A Parallel Imaging and Compressed Sensing Combined Framework for Accelerating High-resolution Diffusion Tensor Imaging Utilizing Inter-image Correlation

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TARGET AUDIENCE Researchers and clinicians interested in accelerated high resolution DWI/DTI

PURPOSE While high-resolution diffusion tensor imaging (DTI) is a powerful tool in scientific studies and clinical diagnosis, prolonged acquisition time has always been obstacles in its applications. Parallel imaging (PI) methods, such as conjugate gradient SENSE (CG-SENSE) [1], have long been applied to diffusion imaging, but their acceleration capability is limited by noise amplification and residual aliasing at high reduction factors. Some recent work has demonstrated great potential of compressed sensing (CS) based techniques, for example joint sparsity CS, in simulations or *ex vivo* studies [2]. In this work, a PI and CS combined framework is proposed, which addresses practical issues of motion error correction and PI calibration in high-resolution DTI, and utilizes inter-image correlation through anisotropic signals for improved sparsity. A specific implementation based on multi-shot variable density spiral (VDS) is used to demonstrate the method in *in vivo* DTI experiment.

THEORY The proposed method consists of three steps, as illustrated in *Fig. 1*: 1) motion-induced phase error estimation, similar as introduced in [1]; 2) initial CS reconstruction, which provides data for calibration of PI kernel and estimation of isotropic signals; 3) final reconstruction combining PI and CS, as formulated by equation (1). The idea of SPIRiT [3] is adopted to combine PI and CS, which is compatible with arbitrary k-space trajectories. The general reconstruction formulation is: $\hat{m}_{i=1,\dots,L} = \arg\min_{m}(\sum_i \|D_i m_i - y_i\|^2 + \sum_i \|G_i m_i - m_i\|^2 + \lambda R(m_{i=1,\dots,L}))$ (1), where m and y is images to be reconstructed and partially sampled k-space data, L is the number of diffusion directions. G_i is the SPIRiT operator, and operator D_i includes sampling mask, (non-uniform) Fourier transform, and motion-induced phase correction. λ is the weight for the CS regularization. $R(m_{i=1,\dots,L})$ is the CS regularization term, and here both intra and inter image correlation is utilized by an anisotropic sparsity model, which further sparsifies diffusion weighted images by removing the isotropic signals $\bar{m} = 1/L\sum_i m_i$. The anisotropic sparsity regularization is formulated as, $R_{AS}(m_{i=1,\dots,L}) = |\Psi\{m - \bar{m}\}|_1$, where Ψ is the sparsifying transform.

METHOD The proposed method, titled as Anisotropic Sparsity-SPIRiT (AS-SPIRiT), was evaluated in a volunteer brain DTI experiment, and compared with CG-SENSE [1]. To demonstrate the benefit of anisotropy sparsity, the same PI-CS combined reconstruction framework integrated with other sparsity models was also implemented for comparison, including L1 and joint sparsity [2] regularized SPIRiT (L1-SPIRiT and JS-SPIRiT). The scan was performed on a Philips 3T system using an 8-channel head coil and multi-shot VDS sequence with α=4. Scan parameters: TR/TE=2500/65ms, FOV=220mm×220mm, b=800s/mm2, number of diffusion direction=6, image resolution=0.86mm×0.86mm, number of interleaves=26, NSA=4. Fully-sampled data were artificially under-sampled with an interleaved sampling pattern in the diffusion dimension. The averaged results with NSA=4 is used as gold standard.

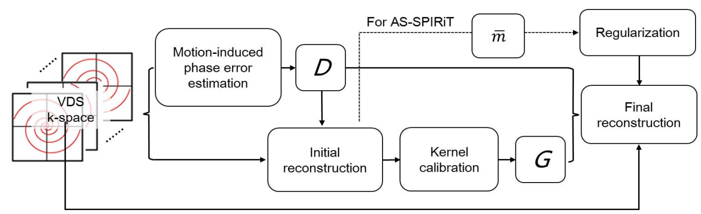

Fig 1. Block scheme of the proposed PI-CS combined reconstruction framework.

RESULTS AND DISCUSSION Representative FA maps reconstructed at R = 3 are compared in *Fig. 2*. The FA maps reconstructed by CG-SENSE are severely degraded by noise. SNR is improved in the results of the PI-CS combined methods. However, in areas of low FA, as pointed by the arrows in *Fig. 2*, false directionality and increased anisotropy appears in the results of L1-SPIRiT and JS-SPIRiT. This error is largely eliminated in the results of AS-SPIRiT. The accuracy of reconstructed FA maps is compared quantitively in *Fig. 3*, which displays whole brain FA error histograms of the above methods at R = 3 and 5. AS regularized reconstruction has an error distribution with the mean value closest to zero and the smallest standard deviation at both reduction factors, which means it has the least bias in FA maps. RMSE of reconstructed FA maps, summarized in *Table. 1*, also demonstrates that AS yields FA maps with highest fidelity. The above results shows that AS utilizes the inter-image correlation of diffusion weighted images in a highly efficient way by exploiting the sparse anisotropic signals.

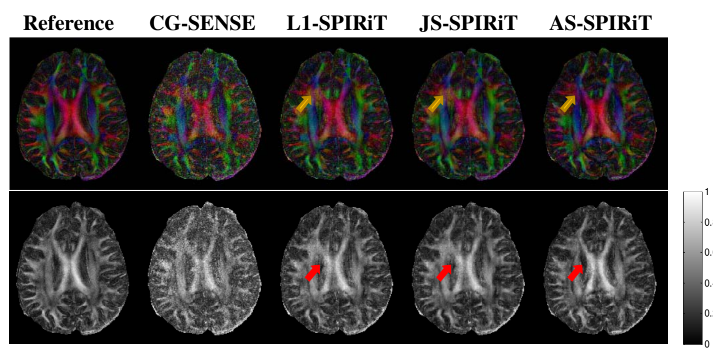

Fig 2. Representative FA and color-coded FA maps at R=3. The yellow and red arrows point out where false directionality appears in the FA maps.

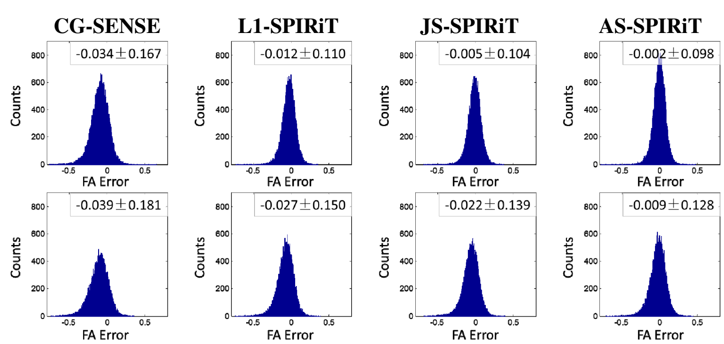

Fig 3. Histograms of FA error at R=3(top row) and 5(bottom row), with mean FA error ± two standard deviations labelled.

CONCLUSION The proposed AS regularized reconstruction can accelerate high-resolution DTI acquisition with high fidelity by effectively combining PI and CS, and utilizing the correlation among different diffusion encoding directions.

	CG-SENSE	L1-SPIRiT	JS-SPIRiT	AS-SPIRiT
R = 3	0.1518	0.0947	0.0880	0.0824
R = 4	0.1728	0.1265	0.1229	0.0943
R = 5	0.1656	0.1340	0.1226	0.1088

Table 1. RMSE of FA maps at R = 3, 4, 5

REFERENCE [1] C Liu et al., MRM 2005; 54:1412-1422. [2] Y Wu et al., MRM 2013; doi: 10.1002/mrm.24721. [3] M Lustig et al., MRM 2010; 64:457-471.