Suppressing mulit-channel diffusion tensor imaging noise using the data consistency constraint

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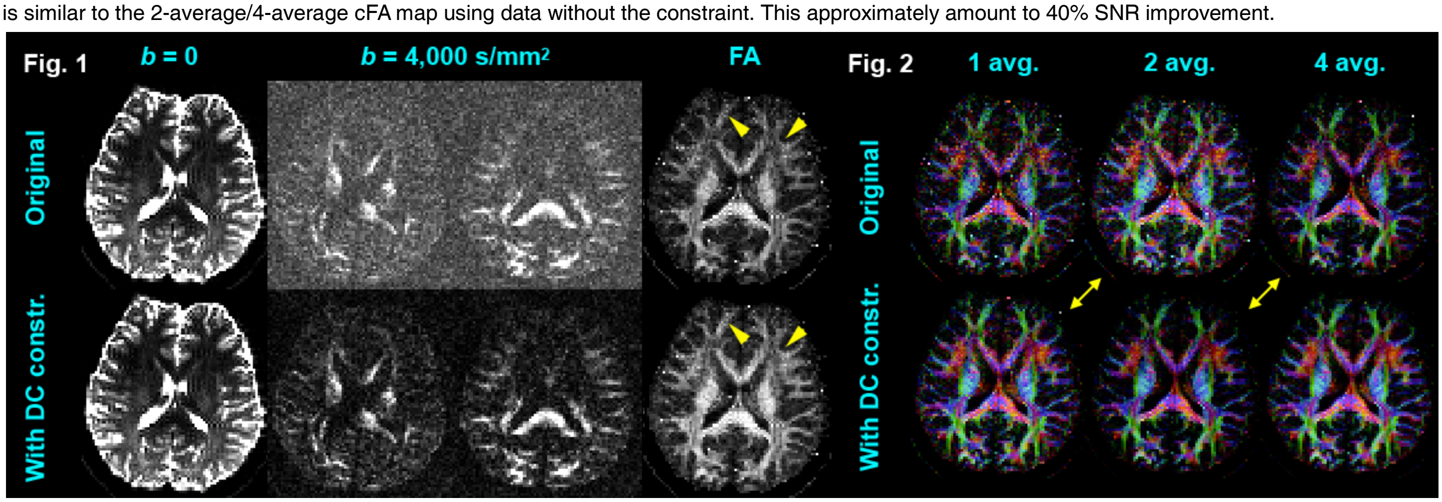
TARGET AUDIENCE Scientists interested in reducing noise in diffusion weighted MRI using data acquired from a coil array.

PURPOSE In parallel MRI (pMRI), the spatial modulation of the signal intensity of array elements has been utilized to accelerate image encoding at the cost of the reduced signal-to-noise ratio (SNR) [1,2]. Alternatively, parallel MRI can exploit the redundancy among channels of a receiver coil array to suppress (motion) artefacts [3-7]. In diffusion tensor imaging (DTI), particularly with high diffusion weighting (*b* value), the image SNR is usually too low to be compromised. Here, we exploit the redundancy among channels of a receiver coil array to improve the SNR of DTI by enforcing a data-consistency (DC) constraint among *k*-space data across receiver coils. Experimental results at 3T with b = 4,000 s/mm^2 demonstrate that the SNR can be improved by approximately 40% by applying this constraint to DTI reconstructions.

METHODS Assuming the coil sensitivity profiles of a MRI detection array are distinct and spatially smooth, each chosen *k*-space data point of a coil can be expressed as the linear combination of the *k*-space data points from all coils at the vicinity of the chosen *k*-space data point. Mathematically, such DC relationship is described as $\mathbf{x} = G\,\mathbf{x}$, where **x** denotes the concatenation of *k*-space data from all coils and **G** is a convolution kernel [8]. Practically, given the *k*-space data across coils, we first estimated the convolution kernel **G** and then reconstructed images at each channel **x** by minimizing the cost function $\mathbf{|Gx\text{-}x|_2+\lambda|Sx\text{-}y|_2}$, where **S** is an index matrix indicating the *k*-space coordinates of the acquired data, **y** is the acquired *k*-space data across all channels, and λ is a regularization parameter. In practice diffusion weighted images were acquired on a 3T MRI scanner and a 32-channel head coil array (Siemens Medical Solutions, Erlangen, Germany). The imaging parameters were: TR=9000 ms; TE= 152 ms, flip angle=90°, b=4,000 s/mm^2, 30 directions; FOV=256x256 mm^2; image matrix:128x128; slice thickness: 3 mm; 37 slices. We used non-diffusion weighted (b=0) image to estimate **G** because it has a higher SNR. Then an iterative reconstruction method based on the conjugated gradient algorithm was used to minimize the cost for each diffusion weighted image. We chose λ =1 in this study. Provided with the diffusion gradient directions, we calculated fractional anisotropy (FA) and color-coded FA (cFA) maps using data reconstructed with and without the DC constraint.

RESULTS Figure 1 shows two diffusion-weighted and one non-diffusion-weighted images with and without using the DC constraint with single-average data. While there was no visible difference in b=0 images, potentially due to their relatively higher SNR, noise was clearly suppressed in b=4,000 s/mm^2 images. Particularly, the white matter signal became more visible in the temporal and frontal lobes (yellow arrow heads), where FA values were more continuous and homogeneous in white matter bundles. We also compared the cFA maps using 1-, 2-, and 4-averge DTI reconstructions (Figure 2). The white matter structure generally has lower noise after applying the DC constraint. Visually 1-average/2-average cFA map using data with the DC constraint is similar to the 2-average/4-average cFA map using data without the constraint. This approximately amount to 40% SNR improvement.



DISCUSSION We proposed a parallel MRI reconstruction algorithm enforcing the *k*-space data consistency such that the noise disturbing such a consistency is suppressed. This method was demonstrated on DTI with a high *b* value (b=4,000 s/mm^2). Different from generating an optimally combined image, out method aims at suppressing noise at each channel in the coil array. The reconstruction was robust across parameters, including the size of the convolution kernel **G** and λ (not-shown). This reconstruction algorithm can also incorporate image sparsity feature. The cost of such algorithm is a longer computational time than the sum-of-squares image reconstruction. Also, the mis-estimated the data consistency relationship (*e.g.*, too small kernel size or noisy data) can also propagate errors into final reconstructed images. Yet our results demonstrate that the image SNR can improve approximately 40% without explicitly estimating coil sensitivity maps.

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