MR Rician Noise Reduction in Diffusion Tensor Imaging using Compressed Sensing by Sampling Decomposition

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INTRODUCTION

MRI magnitude images are often corrupted by Rician distributed noise and a contrast-reducing signal-dependent bias [1]. Reduction of Rician noise is desirable, especially in low signal-to-noise ratio (SNR) images such as those found in diffusion tensor imaging (DTI). Many methods have been proposed to reduce noise in diffusion weighted imaging (DWI), including maximum likelihood estimation (MLE) using a noise model [2]. It is desirable to reduce noise on the front end, independent of the parameter estimation process and to preserve structure. Compressed Sensing (CS) is an image reconstruction algorithm that allows undersampling by acquiring fewer incoherent frequency samples (or so called k-space) [3]. Although CS holds the potential to reduce noise in MR images [3], to date systematic investigation on the capability of CS to reduce MR Rician noise, especially in DWI, is incomplete.

METHODS

Full k-space samples of MR image were first decomposed into multiple sets of incoherent k-space subsamples by applying complement random masks with equal sampling ratio. All k-space samples are utilized in at least of the decompositions. Data decomposition was performed in both the phase encoding (PE) and the frequency encoding (FE) directions. CS reconstruction was applied on each subset of k-space to recover a full k-space. Finally, all CS reconstructed full k-space datasets were aggregated to produce the final, noise reduced, k-space data.

Two datasets were used to evaluate the effectiveness of the proposed method. One was a numerical phantom corrupted by synthetic Rician distributed noise, created by adding independent Gaussian white noise to both the real and imaginary channels of k-space signals [1]. The second was a diffusion tensor MRI data set of a hamster heart with fibrotic scars [4]. DWI images were acquired on a 9.4 T vertical bore magnet (Bruker Biospin, Billerica, MA) at room temperature with a standard Stejskal–Tanner spin-echo pulse sequence. Seven 1 mm thick short-axis slices were acquired to cover the whole left ventricle. In-plane resolution was 102x102 μm^2. A diffusion tensor matrix and the three corresponding eigenvalues were calculated from the diffusion-weighted images using in-house Matlab software. In the current study, the diffusion-weighted image set was de-noised by the proposed method prior to the calculation of diffusion tensor and corresponding eigenvalues. A fractional anisotropy (FA) map was generated based on the three eigenvalues as a measure of the diffusivity in different directions, following the proposed method for further direct noise reduction.

RESULTS

CS reduced Rician noise in both the numerical phantom magnitude image and cardiac DWI data (Figs 1 and 2). CS without sampling decomposition (i.e. CS reconstruction with full samples), did not reduce Rician noise, but CS with 2 decompositions significantly reduced noise. At a higher decomposition factor of 4, noise was reduced even more at the expense of blurring and a "halo" artifact. CS parameters values [TV weight, L_1 weight] of [2×10^{-6}, 1×10^{-10}] were used. Compared with the original, low SNR FA map, the FA map generated from noise reduced DWI images showed improved delineation of anatomical structure (Fig. 2c). From other results, we believe that dark regions in the FA map are fibrotic areas, with expanded extracellular space, and that bright regions correspond to calcium deposition in fibrotic areas [4]. The de-noised FA map showed much sharper contrast so that the fibrotic area can be more easily characterized by visual inspection (Fig. 2c). To further facilitate the reading of FA map, the noisy background of the FA map can be further suppressed by direct application of the proposed method using larger CS parameter values [TV weight, L_1 weight] of [2×10^{-1}, 1×10^{-1}] and 2 decompositions (Fig. 2d).

CONCLUSIONS

We conclude that for fully sampled data, CS with sampling decomposition can reduce MR Rican noise. The proposed method significantly reduces MR Rician noise using just 2 decompositions. More decompositions can further reduce noise but at the expense of blurring. The FA map in DTI was significantly improved by the proposed method. Alternatively, CS acquisition/processing can be used to reduce image acquisition time by reducing the number of averages. Another potential application is Kurtosis imaging for which effective de-noising is highly desirable due to large b-values used [5]. The computational cost of our method should not be a limitation for its application due to development of fast CS algorithms [6], parallelization of the CS processes, and GPU acceleration.

ACKNOWLEDGEMENTS This work was supported under NIH grant R01-EB004070, the Research Facilities Improvement Program Grant NIH C06RR12463-01, and an Ohio Biomedical Research and Technology Transfer award, "The Biomedical Structure, Functional and Molecular Imaging Enterprise."

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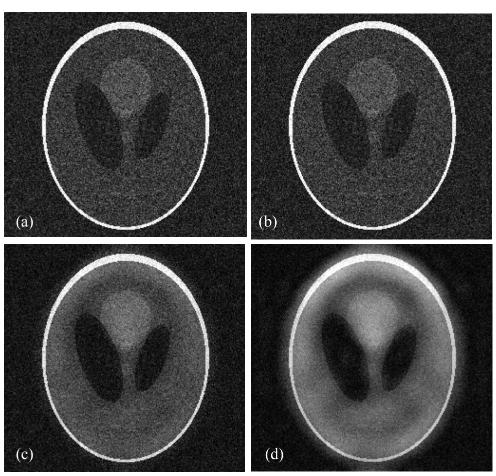

Fig. 1. (a) Phantom image with Rician noise added. (b) Image following CS without sampling decomposition remains noisy. Images (c)-(d) were processed by the proposed method with k-space decomposition numbers of 2 and 4, respectively. Rician noise was obviously reduced. Identical compressed sensing parameters were used for reconstructing images (b)-(d). Increasing the decomposition factor reduces Rician noise at the expense of blurring and a "halo" artifact.

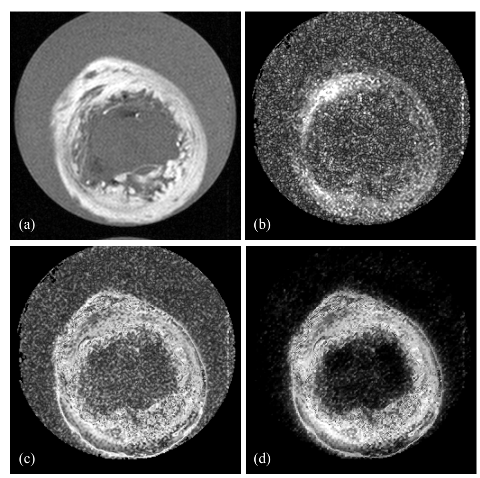

Fig. 2. (a) is a DWI image of a hamster heart. (b) is the originally estimated FA map which is so noisy that tissue structure is hardly identified. (c) is the FA map estimated from denoised DWI data by the proposed method. Noise is significantly reduced and more tissue structures are revealed. By applying the proposed method directly to FA map (c), noisy background is almost removed as demonstrated in FA map (d).