Adaptive Compressed Sensing MRI

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INTRODUCTION

Most of the prior work in compressed sensing MRI has been based on pre-defined transformations to sparsify image representations, e.g. discrete cosine transforms (DCT), wavelets, and finite differences [1]. Even though an analytical transformation usually features a fast implementation, its performance as a sparsifying transform is limited by the underlying basis functions, which tend to be over-simplistic for real images. Recent work on sparse signal representation based on learning the basis functions from the signal itself has demonstrated improved performance over analytical functions. For example, the K-SVD method [2] uses image patches to get very sparse representations. This method was originally proposed for image denoising. In this work, we propose to adapt the sparsifying transform during the reconstruction process based on the K-SVD method in order to increase sparsity of image content and thus enable higher accelerations and/or improve image quality.

METHODS

Image reconstruction in compressed sensing (CS) [1] is given by: $\min_{\mathbf{m}} \|\mathbf{Dm}\|_{0 \text{ or } 1} \; s.t. \|\mathbf{y} - \mathbf{Fm}\|_2 \le \varepsilon$, where $\mathbf{D}$ is the sparsifying transform or dictionary, $\mathbf{m}$ is the image to reconstruct, $\mathbf{y}$ is the acquired data and $\mathbf{F}$ is the undersampled Fourier transform. The algorithm searches for the sparsest image representation under the dictionary $\mathbf{D}$ subject to data consistency constraints. In this work, reconstruction of a 2D image with acceleration along k_y was assumed. The 1D-image examples to adapt the dictionary $\mathbf{D}$ were given by the columns of the undersampled image. The combined reconstruction and dictionary update problem was solved iteratively, where each iteration included two stages: (a) sparse recovery and (b) dictionary update. In the first stage, the dictionary $\mathbf{D}$ was fixed and compressed sensing reconstruction was solved by using the Orthogonal Matching Pursuit (OMP) approach [3]. OMP was applied on a column-by-column basis to get the sparse weights $\hat{\mathbf{W}}$. In the second stage, the dictionary was updated using the K-SVD algorithm [2] using the computed sparse weights. The dictionary update represents a least-squares fit to the columns of the reconstructed image in the previous stage. The dictionary $\mathbf{D}$ was initialized using a 4-tap Daubechies wavelet transform. The compressed sensing reconstruction from the first iteration represented the standard CS result.

A fully-sampled brain image was employed to test the combined reconstruction and dictionary learning approach. Acceleration factor of 2.5 along the k_y dimension was simulated with a random undersampling pattern to generate the required incoherence for compressed sensing.

RESULTS

Figure 1 shows the improved reconstruction performance of adaptive CS over the standard CS approach. The root mean square values with respect to the fully-sampled image were 13.5% for standard CS whereas 6.2% for adaptive CS. The combined reconstruction and learning was performed using 50 iterations of the K-SVD algorithm. The reconstruction artifacts are mainly associated with small coefficients in the sparse domain that are deeply submerged in the interference created by the random undersampling pattern. Adapting the sparsifying transform to sub-image examples helped to separate better these small components from the interference, which resulted in improved image quality.

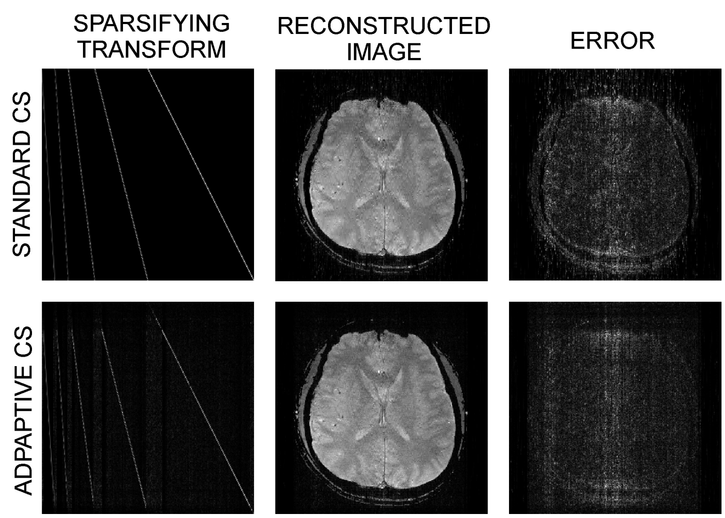

Figure 1: Reconstruction example for standard and adaptive CS with simulated acceleration along the k_y dimension (R = 2.5). Standard CS was performed with a 1D-Wavelet transform (each column represents a different basis function). The adaptive CS approach adapted this initial transform to increase sparsity according to sub-image examples.

DISCUSSION

Adapting the sparsifying transform to better represent examples extracted from the accelerated data results in increase sparsity of representation and thus improved compressed sensing reconstruction. This work demonstrated feasibility of the method using 1D-image patches as signal examples to update the dictionary. Future work will explore the use of 2D sub-image patches and parametric models for the basis functions in order to further increase the sparsity of image representation.

GRANT SPONSOR: NIH R01-EB000447.

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