Region of Interest Compressed Sensing

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Introduction: Compressed sensing (CS) MRI has been used to achieve satisfactory image reconstructions from fewer k-space samples as compared to traditional (i.e. Nyquist-sampled) methods [1]. To do this, CS relies on an assumption of transform sparsity of the image. However, if the signal is not *strictly* transform sparse, as is the case for most MR images, the mismatch between assumption and reality introduces errors into the CS reconstruction. These errors manifest as image artifacts, and there is concern that this could lead to misdiagnoses (e.g. false negatives) when applied clinically. In this work, we utilize the CS framework but only impose the transform sparsity constraint *outside* of a region of primary clinical interest (ROI), where small errors can be tolerated. With this approach, we exploit the benefits of CS while avoiding image artifacts within the ROI.

Theory: CS reconstruction is typically performed by solving the optimization problem in Eqn. 1, where λ is the regularization parameter that determines the tradeoff between data consistency and ℓ_1-regularization, *s* are the sampled k-space data, Φ is the sampling matrix with fewer rows than columns, Ψ represents the sparsifying transform, and *c* is a matrix of transform domain coefficients such that the image $m = \Psi * c$. Many works [2,3] have proven that, in the noiseless case, perfect reconstruction is possible if the true *c* contains only a few nonzero terms. However, rather than exhibiting strict sparsity, the transform coefficients of MR images more typically decay with respect to a power law. In this case, Candes et al. show that, even in the noiseless setting, signal recovery via CS is not error-free [4]. As Lustig et al. have discussed, the errors may be attributed to the tendency of CS reconstruction to underestimate the magnitudes of the transform coefficients. This results in a reduction of image contrast [1]. To avoid these artifacts in the ROI, we propose a modified cost function seen in Eqn. 2, where $\{i: \psi_i \notin \text{ROI}\}$ is the set of basis functions that are zero-valued everywhere within the ROI. Thus, if a basis function ψ_j is non-zero anywhere within the ROI, its transform coefficient c_j is not constrained by the ℓ_1-regularization term.

$$\min_{c} \|s - \Phi\Psi * c\|_2^2 + \lambda\|c\|_1$$

Equation 1: CS Reconstruction

$$\min_{c} \|s - \Phi\Psi * c\|_2^2 + \lambda \sum_{\{i:\psi_i \notin \text{ROI}\}} |c_i|$$

Equation 2: Proposed Method

Methods and Results: Experiments were conducted on a GE Signa 3T EXCITE HDx system. An inversion recovery GRE sequence was used to collect Nyquist-sampled k-space data of a mid-sagittal slice of the brain, as seen in Figure 1. In applying CS, the k-space data were downsampled along the phase encode (PE) direction using a variable density scheme that favored sampling of the PE lines closer to the origin. We used the Daubechies(4,4) wavelet transform as the sparsifying transform. In applying our method, we followed the same steps with one important exception. After choosing the ROI, we determined which wavelet basis functions had at least one non-zero value within the region. For those functions, we did not impose the ℓ_1-penalty on their coefficients. Figure 2 shows the ROI from reconstructions for two different acceleration factors. Figure 3 shows 1D profiles of the ROIs.

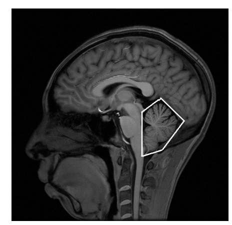

Figure 1: reference image (contour identifies the ROI)

Discussion: In Figure 2, one sees that the ROIs in our proposed method appear sharper and more similar to the reference ROI. In Figure 3, the arrows highlight areas in which the CS reconstruction significantly underestimates the true value, resulting in a loss of contrast across the image. The magnitudes of these peaks and valleys are more accurately estimated when using the proposed method. Additionally, the slopes of the lines when transitioning from peak to valley are also more accurately estimated by the proposed method, resulting in the sharper images seen in Figure 2. We note that our concept has its limits. For example, the ROI cannot be the entire image, else our proposed cost function would reduce to an ill-posed least-squares problem, which does not utilize the benefits of the CS theory. In further work, we plan to explore the performance degradation as a function of increased ROI area.

Conclusion: CS reconstruction can introduce image artifacts that may be costly in clinical applications. We show that by imposing the sparsity constraint only outside of a ROI, we are able to increase the ROI reconstruction quality without sacrificing the acceleration gain.

References: [1] Lustig et al., MRM 2007;.[2] Tropp, IEEE IT 2006; [3] Candes et al., IEEE IT 2004; [4] Candes et al., IEEE IT 2004;

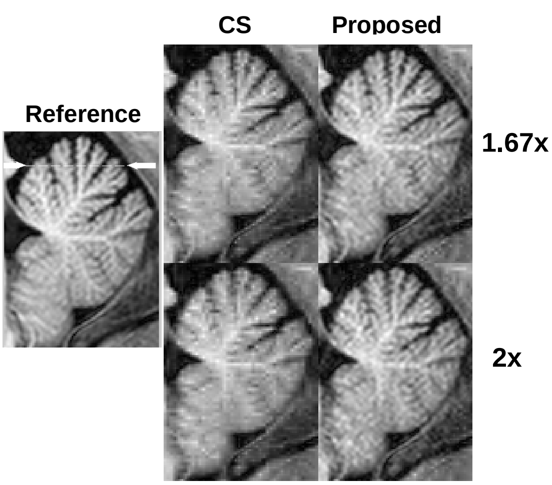

Figure 2: Reconstruction of ROIs. Reference uses Fourier reconstruction of Nyquist-sampled data

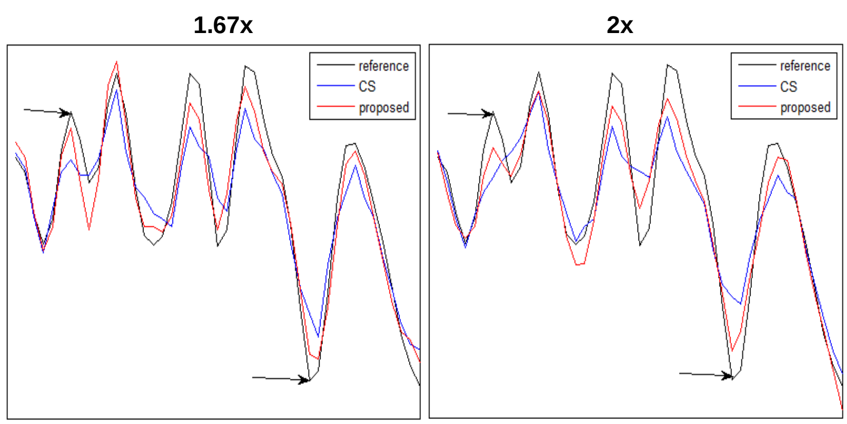

Figure 3: 1D signal profiles. Location of signal profile is denoted by arrows in reference image of Figure 2. Reference uses Fourier reconstruction of Nyquist-sampled data.