Accelerated 3D phase-contrast imaging using adaptive compressed sensing with no free parameters

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Introduction Compressed Sensing (CS) theory [1] allows one to use the sparsity of images in a transform domain (e.g. wavelets) effectively to enable image reconstruction with sub-Nyquist sampled data. While CS methodologies present several potential benefits for medical imaging applications (e.g. reduced scan times, higher resolution imaging, etc.), their successful implementation on clinical scanners will require robust algorithms that can automatically account for patient-to-patient and anatomical variability in the images. Typical image reconstruction algorithms employing CS theory in the literature are iterative in nature and solve the problem of minimizing a cost function consisting of an L2-norm error (or data consistency) term and one or more L1-norm terms that impose the transform domain sparsity constraints. In particular, two classes of algorithms are commonly used: (1) Non-linear conjugate gradient (NLCG) [2], and (2) iterative soft thresholding (ST) [3] approaches. The NLCG method has good convergence properties, but is sensitive to the choice of relative weights on the L1-norm penalty terms that have to be selected empirically on a case-by-case basis. NLCG algorithms may also involve computationally intensive cost function / derivative evaluations and line searches. The ST approach in the wavelet domain is leaner to implement but is also sensitive to the choice of the thresholding parameter and is slow to converge. In this paper we describe a robust and fully data driven approach to CS reconstruction in the ST framework that uses a Nesterov type [4,5] 2-step optimal gradient scheme for fast convergence properties along with adaptive wavelet denoising for imposition of the L1-sparsity constraint. For illustration we combine this CS algorithm with image domain parallel imaging (SENSE) and apply it to brain vasculature phase-contrast imaging. The reconstructed angiograms were scored blindly for image quality by an experienced neuroradiologist.

Methods In describing our approach for combining the CS algorithm with parallel imaging, the data acquired for each of the echoes from a 3D phase contrast pulse sequence may be represented as $y_j = \Phi_{FT}\Phi_{CSP,j} f$ where y_j is a vector of k-space measurements from the j-th coil, *f* is the image to be determined, Φ_{FT} is the Fourier transform and $\Phi_{CSP,j}$ is coil sensitivity weighting of the j-th coil. If *f* is compressible in basis Ψ, incoherent with Φ_{FT} and $\Phi_{CSP,j}$: $y_j = \Phi_{FT}\Phi_{CSP,j}\Psi s = \Phi_M s$. The number of measurements $Y=\{y_1,\ldots,y_J\}$ may be greatly reduced from the Nyquist rate, if the representation *s* of the image in the Ψ domain is sparse. The task is to recover *s*, the coefficients of *f* projected onto the basis Ψ. For each of the echoes we reconstruct *s* with the following iterative loop: $s^{n+1} = T_\lambda\{\, w^n + \Phi_M^H (\, y - \Phi_M w^n)\}$, where $w^n = \; a(n)s^n + b(n)s^{n-1}$ is a linear combination of solutions from two prior iterations (as opposed to the nominal case when only s^n is used for the update), and $T_\lambda\{\, w\}$ denotes a level-dependent adaptive soft thresholding operation. In particular, we used the Nesterov optimal gradient scheme [4] for selecting the coefficients *a(n)* and *b(n)* of the linear combination above. The two starting guess solutions were initialized as: $s^0 = 0$, and s^1 = wavelet coefficients of the zero filled solution. We would like to emphasize that the procedure described above does not require tuning of any free parameters. An important advantage of the 2-step update is its fast-convergence property [4,5], which allows one to use standard wavelet denoising methods (e.g. SURE threshold [6]) to impose the sparsity constraint instead of tuning the thresholds over iterations to select the most significant wavelet coefficients [7,8].

Results and Discussion Brain vasculature data were acquired on five healthy volunteers who gave informed consent, using a 3T GE MR750 scanner with 8-channel head coil and a 3D phase contrast pulse sequence with 25 cm field of view. Four echoes were acquired with the sign of the first flow-sensitizing gradient moment in x, y, z directions given by { - - -, + - -, - + -, - - +}. Full Nyquist sampled data were collected and later synthetically undersampled in ky-kz planes for each encoding x location. A Gaussian density distribution was used for selecting the sample locations with a dense sampling window in the center of ky-kz space for estimating the coil sensitivities. Complex Difference (CD) processing [9] was then used to obtain the flow images from the 4 echo images. The reconstructions using the 2-step ST algorithm for the different datasets did not require any tuning of parameters in the algorithm – the necessary threshold values were selected adaptively in a completely data driven manner. The iteration was stopped when the change in L2-error norm was less than 0.05% in successive iterations. For illustration, we show sagittal MIP images for one dataset undersampled by a factor of 4 and reconstructed with a 1-step ST (using only one prior guess solution for update) with SURE threshold, an empirically tuned NLCG approach (wavelet and TV penalties), and the 2-step ST method with SURE threshold, with the same number of iterations (20), in each case. While both 1-step and 2-step ST approaches with SURE thresholding do not have free parameters, the slow convergence of the 1-step ST approach causes loss of some of the details/sharpness in the image when compared with the NLCG solution for the same number of iterations. The 2-step ST solution in Fig. 1(c) is however seen to be comparable to that from an empirically tuned NLCG reconstruction Fig 1(b). We reconstructed the remaining four datasets with NLCG with the parameters optimized for the first dataset and with the 2-step method described above for acceleration factors of 4 and 6. The reconstructed MIPs were presented in a blinded fashion to a neuroradiologist who scored the images on a 1-5 scale. The scores were analyzed for statistical significance and the results are presented in Table 1.

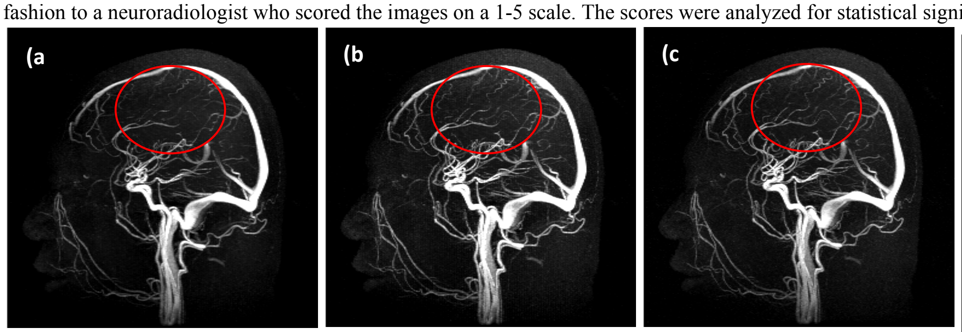

Fig. 1: Sagittal MIP images for 3D vascular phase contrast reconstructions with acceleration factor (R = 4).
(a) ST with single step update (b) Empirically tuned NLCG (c) 2-step ST with SURE thresholding

Table1: Statistical analysis of image quality scores of MIPs (3 MIPs x 5datasets)

Acceleration Factor	Average Score	Standard Deviation
R = 1	4.5	0.5
R = 4 (NLCG)	2.5	0.5
R = 4 (ST)	2.9	0.5
R = 6 (NLCG)	2.0	0.5
R = 6 (ST)	2.3	0.6
p-values for two-tailed paired t-test: 0.03 (R=4), 0.04 (R = 6)		

While the sample size is relatively small and only one kind of imaging sequence and contrast mechanism was considered, the results of the paired t-test indicate that the adaptive approach is more robust than NLCG with a single choice of tuning parameters for all volunteers. Even in the case of the dataset used to tune the NLCG reconstruction, the average score is slightly higher for the ST reconstruction, hinting at an imperfect choice of tuning parameters for NLCG reconstruction and stressing the importance of an automated, data-driven selection of said tuning parameters.

In conclusion, we have presented a practical method for CS image reconstruction based on iterative soft thresholding (ST) with data-driven, adaptive selection of these parameters to account for patient-to-patient or anatomical variability. The improved robustness of this method over the NLCG approach without dataset-by-dataset tuning of free parameters is illustrated with an initial statistical analysis of image quality scores for a five-volunteer study.

References: [1] Candes et al., IEEE Trans. Info. Theory 52, 489 (2006),[2] Lustig et al. MRM, 58, 1182 (2007),[3] Daubechies et al, Comm. Pure Appl. Math 57, 1413 (2004), [4] Y. Nesterov, Soviet Math. Dokl. 27(2): 372-376 (1983), [5] A. Beck, M. Teboulle, SIAM J. Imag. Sciences, 2, 183(2009), [6]S. Mallat, *A Wavelet Tour of Signal Processing*, [7] K. Khare, et al, ISMRM 2009, 2835 [8]K. King, et al, ISMRM 2009, poster 2822, [9] MA Bernstein, et al, MRM 32, 330(1994).