Low-dimensional-Structure Self-Learning and Thresholding (LOST): Regularization Beyond Compressed Sensing for MRI Reconstruction

M. Akcakaya[1], T. Basha[1], B. Goddu[1], L. Goepfert[1], K. V. Kissinger[1], V. Tarokh[2], W. J. Manning[1], and R. Nezafat[1]
[1]Medicine, Beth Israel Deaconess Medical Center, Harvard Medical School, Boston, MA, United States, [2]School of Engineering and Applied Sciences, Harvard University, Cambridge, MA, United States

Introduction: Lengthy acquisition time is one of the main challenges of MRI, especially for imaging the coronaries, and acceleration rates beyond what is available with parallel imaging is appealing. Compressed sensing (CS) has been recently applied to accelerate image acquisition in MRI [1,2]. Although sparsity is a necessary condition for conventional CS reconstruction, it is not possible to know whether a transform can efficiently represent various image characteristics of an anatomy. For instance, wavelets cannot capture smooth transitions sparsely, whereas finite differences have problems with sharp edges. In this study, we seek to develop an improved image reconstruction method that utilizes the structure (anatomical features) in the image being reconstructed.

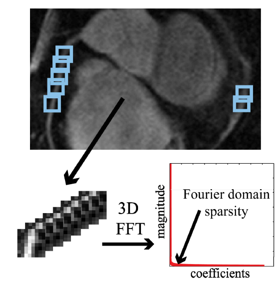

Fig. 1: *Coronary images have similar signal content at various spatial locations. These similarity clusters (SCs), as 3D objects, are highly sparse in Fourier domain.*

Theory: The proposed algorithm, *lo*w-dimensional-structure *s*elf-learning and *t*hresholding (LOST) learns the image areas of similar signal characteristics and uses this information for reconstruction. Initially, low resolution images are generated from the fully acquired center of k-space. Using these images, 2D image patches of similar signal content are grouped into "similarity clusters" (SCs), utilizing a technique called block matching [3], with l_2 distance between blocks as similarity measure. Then an iterative approach is used, where data consistency with measured data is enforced and the data-consistent image estimate is de-aliased. Traditionally, de-aliasing is done by soft-thresholding in a fixed transform domain (e.g. wavelet) [2]. In LOST, SCs are thresholded based on their low-dimensional properties to remove aliasing and artifacts. When the 2D blocks in a SC are stacked into a 3D structure, and a 3D FFT is applied, the data is sparse (**Fig. 1**): The 2D FFT applied to each block promotes sparsity within the block, and FFT along third dimension of SC greatly enhances sparsity since the 2D blocks have similar content [3]. This adaptively-learned sparsity property is used to threshold aliasing artifacts. In LOST, we use shrinkage based on hard thresholding (ht) in early iterations to reduce aliasing artifacts and Wiener filtering (Wie) later to reduce blurring artifacts [3] (**Fig. 2**). Since clusters are not necessarily disjoint, there are multiple thresholded estimates for 2D blocks. These are combined using weighted averaging.

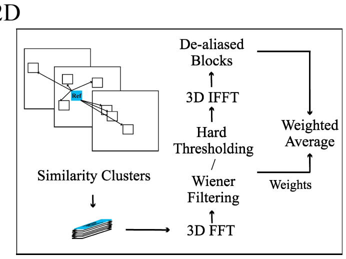

Fig. 2: *LOST learns SCs, uses their Fourier sparsity to remove aliasing.*

Methods: The acquired data in j^{th} coil is $\mathbf{S}_j = \mathbf{F}_\Omega(\mathbf{m}_j)$, where $\mathbf{m}_j$ is the image, F_Ω is the partial unitary Fourier operator. The iterative part is implemented as follows: at iteration t, (a) calculate $\mathbf{U}_j^{(t)} = \mathbf{F}(\mathbf{m}_j^{(t)})$; (b) replace $\mathbf{U}_j^{(t)}$ at Ω with $\mathbf{S}_j$; (c) compute $\mathbf{F}^{-1}$ of $\mathbf{U}_j^{(t)}$; (d) generate $\mathbf{m}_j^{(t+1)}$ by LOST shrinkage. Proposed algorithm was implemented in two stages: 1) SCs are learnt from low-resolution images generated from central k-space using a Hanning window, and iterative algorithm is applied (25 iterations) using these clusters with ht, generating $\mathbf{m}_j^{\mathrm{I}}$. 2) Clusters are learnt from $\mathbf{m}_j^{\mathrm{I}}$, and iterative algorithm is applied (15 iterations) alternating between ht and Wie. Algorithm parameters are fixed for all reconstructions.

Retrospective coronary MRI: Images were acquired on a 1.5T Philips Achieva with 5-channel cardiac coil using an SSFP imaging sequence. Right and left coronaries were imaged using a targeted small slab acquisition in 10 healthy adult subjects using a fully sampled k-space. The exported k-space data were undersampled by factors of 2, 3 and 4; keeping the center 50×5 k_y-k_z lines, and randomly discarding edges. Images were reconstructed with proposed method and l_1 minimization CS using Daub4 wavelets [2,4]. The final estimates were generated by root-sum-squares of the coil estimates.

Prospective coronary MRI: The coronary arteries were imaged in 4 healthy subjects, with prospective undersampling rates of 2, 3 and 4 using the same SSFP sequence. The phase ordering scheme was modified to accommodate random undersampling, while mitigating eddy current and flow artifacts. Images were also acquired using uniform undersampling with SENSE for comparison [5].

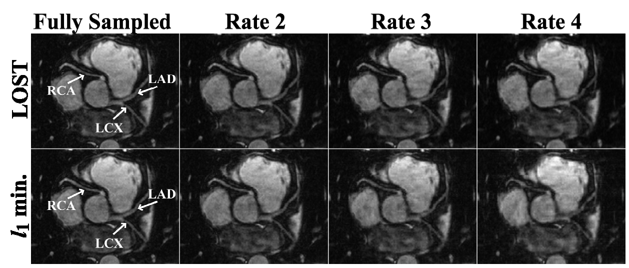

Fig. 3: *Retrospective under-sampled left coronary reconstruction using LOST and l_1 CS.*

Results: Example left coronary images from the retrospective study is shown in **Fig. 3**. LOST images exhibit less artifacts, reduced blurring, superior quantitative sharpness, and higher subjective score by a blinded reader ($p<0.05$) when compared to l_1 minimization. The example RCA images from the prospective acquisition are shown in **Fig. 4**. LOST provides visible improvements over both l_1 minimization and SENSE with less blurring and noise.

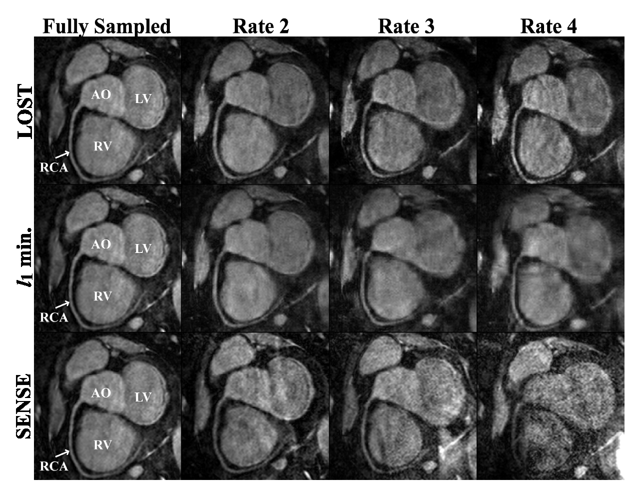

Fig 4: *Prospective accelerated coronary MRI acquisition, demonstrating superior LOST reconstruction.*

Conclusions: We have developed and assessed an image reconstruction technique for accelerated imaging that utilizes the structure of images being reconstructed without need for training data. The proposed method offers improvements over existing CS and parallel imaging techniques in coronary MRI.

Acknowledgements: The authors acknowledge grant support from NIH R01EB008743-01A2, AHA SDG-0730339N, and Harvard Catalyst.

References: [1]Block,MRM,2007;[2]Lustig,MRM,2007;[3]Dabov,IEEE TIP,2007;[4]van den Berg,SIAM JSC,2008;[5]Pruessmann,MRM,1999.