ACCELERATING T2 MAPPING VIA UNDER-SAMPLED LOW-DIMENSIONAL-STRUCTURE SELF-LEARNING AND THRESHOLDING (LOST) RECONSTRUCTION

Tri Minh Ngo[1], Haiyan Ding[2], Mehmet Akçakaya[3], Elliot R. McVeigh[1], and Daniel A. Herzka[1]

[1]Biomedical Engineering, Johns Hopkins School of Medicine, Baltimore, MD, United States, [2]Biomedical Engineering, Tsinghua University, Beijing, China, [3]Beth Israel Deaconess Medical Center, Harvard Medical School, Boston, MA, United States

Introduction: Myocardial 3D T_2 mapping is useful for differentiating between infarct, edema and normal tissue. However, generating 3D T_2 maps requires acquiring multiple complete 3D datasets with different T_2 weightings resulting in long acquisition times[1]. Reconstruction methods which incorporate prior knowledge of image structure may enable reconstruction from fewer measurements reducing acquisition time thus making quantitative T_2 measurement more clinically relevant. Compressed sensing (CS) methods can reconstruct high fidelity images from under-sampled datasets typically by incorporating prior knowledge that the image of interest is sparse, i.e. compressible, in some basis, e.g. wavelets[2]. Recently, reconstruction methods which incorporate knowledge that the image is patch-wise self-similar have demonstrated improved performance over standard sparsifying transform based reconstructions[3]. Here we apply Low-dimensional-structure self-learning and thresholding (LOST)[3] to reconstruct under-sampled T_2 mapping dataset and compare with SENSE reconstruction with equivalent acceleration rates.

Methods: We acquired a fully sampled dataset from an *ex-vivo* porcine heart containing an infarct. Four interleaved volumes were acquired with varying T_2 Prep TEs =35, 40, 45, 50 ms resulting in a differentially weighted dataset suitable for T_2-mapping[1]. Other imaging parameters were: TR/TE 4.3/2ms, flip angle 18°, simulated diastolic window 65.2ms for a simulated heart rate of 60 BPM, FOV 130×138×100mm^3, voxel size 2×2.3×4.0 mm^3, 8 channel head coil and matrix size of 128x60x32. This fully sampled dataset was retrospectively under-sampled, retaining only 33.3%, 26% of the original phase encodes in the ky, kz directions, corresponding to an acceleration rate of approximately R3, R3.9 respectively. First, we fully sample a rectangular 20 ky x 10 kz region at the center of k-space. For SENSE reconstructions, the remaining sampled phase encodes are selected regularly: (R3) R2 in ky,kz; (R3.9) R3 in ky, R2 in kz. For LOST reconstructions the remaining phase encodes were selected randomly from a normal distribution centered at the k-space origin, with each echo having a different sampling pattern. The coil sensitivity profile used for all reconstructions was estimated from the fully sampled center of k-space after multiplying with a Kaiser window to reduce Gibbs ringing artifacts. Each differentially T_2 weighted image was reconstructed independently. The fully sampled data set was reconstructed using R1 Generalized Encoding Matrix (GEM) SENSE [4], i.e. multiplying the acquired data by the pseudo-inverse of an encoding matrix which incorporated the sensitivity profiles and all Fourier basis functions. The under-sampled auto-calibrated SENSE reconstructions were similarly performed using GEM SENSE, but only including Fourier basis functions corresponding to the sampled k-space locations into the encoding matrix. The under-sampled LOST reconstructions were performed in stages. First the coils were combined using R1 GEM SENSE. Under-sampling aliasing artifacts in the resulting coil combined image were then removed using LOST thresholding (parameters: threshold=0.03, Nb = 4; Ngroup = 16; Nsearch = 8; Ndepth = 1). Data consistency was then enforced on a per-coil basis for the sampled k-space locations. These steps were repeated for 100 iterations. T_2 maps and goodness of fit R^2 parameters were computed by linear regression through log-transformed data. Pixels with regression coefficient $R^2<0.9$ were rejected, as lower R^2 represent a poor fit to the exponential function from possible corruption of the underlying data through noise/subsampling/reconstruction.

Results: *Global reconstruction Error:* Figure 1 compares a representative slice from the reconstructed T_2 weighted volume corresponding to T_E=35ms and the T_2 map computed from all reconstructed differentially T_2 weighted volumes for the fully sampled, SENSE and LOST methods. At R3 SENSE preserves edge details better than LOST but has noise amplification. At R3.9 SENSE exhibits high noise amplification degrading the resultant T_2 map, resulting in many pixels which don't fit the exponential decay model. The LOST reconstruction exhibits blurring of high spatial frequency features but preserves the exponential decay better with increasing acceleration. *Distribution of errors:* Figure 2 compares the SENSE and LOST pixel-wise distribution of T_2 errors for pixels with $R^2>0.9$. Table l lists the mean and standard deviation of pixels with a goodness of fit $R^2>0.9$. Additionally, Table 1 lists the ratio of total pixels with $R^2>0.9$ in the respective reconstruction to total pixels with $R^2>0.9$ in the fully sampled reconstruction. For acceleration rates R3 and R3.9, the mean pixel-wise T_2 error for LOST is lower than SENSE.

Conclusion: We find that for acceleration rates R3 and R3.9, the mean T_2 error is lower for LOST than SENSE. At rate R3 SENSE reconstructs edge details better than LOST even though SENSE's mean T_2 error is higher. At rate R3.9, the SENSE matrix is poorly conditioned, resulting in high noise amplification while LOST reconstruction exhibits blurring of high frequency details. Further testing with retrospectively and prospectively under-sampled in-vivo datasets is needed to validate the viability of the proposed reconstruction strategy for clinical use.

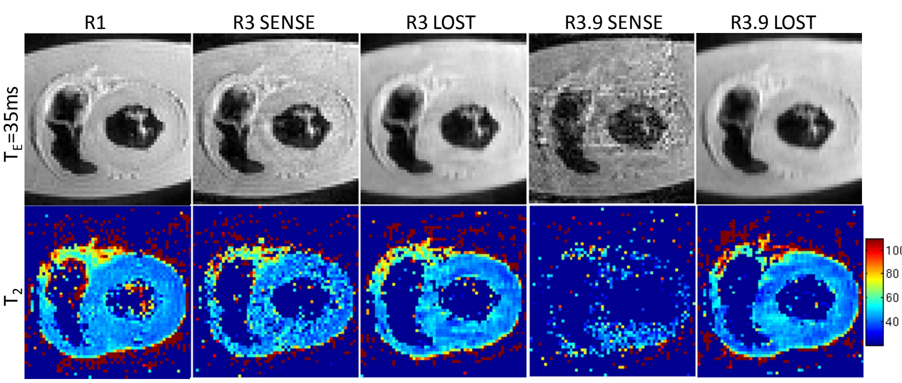

Figure 1: Representative slice of reconstructed 3D T_2 weighted, T_E=35ms (top row) and estimated T_2 map (bottom row) volumes. (Columns left to right) Fully sampled, R3 self calibrated SENSE, R3 LOST, R3.9 self calibrated SENSE, R3.9 LOST reconstructions. SENSE dataset was regularly under-sampled while LOST was Gaussian under-sampled. Pixels with goodness of fit $R^2<0.9$ were set to zero for display purposes.

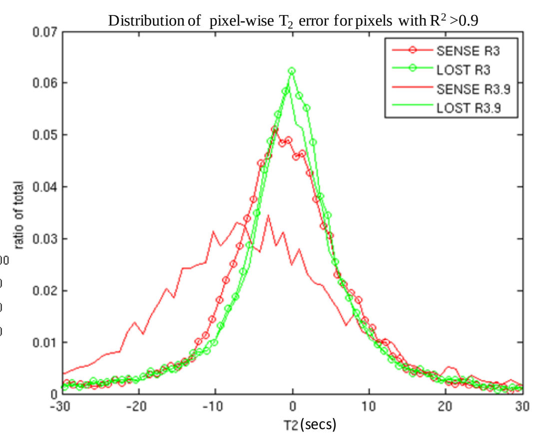

Figure 2: Distribution of pixel-wise T2 error for pixels with $R^2>0.9$ in entire volume for R3, R3.9 SENSE and LOST reconstructions.

Table 1: Comparison of T_2 error statistics and quality of T_2 model fit for R3.9 accelerated SENSE and LOST

	R3 SENSE	R3 LOST	R3.9 SENSE	R3.9 LOST
T_2 error mean±std	-4.44±24.70	-3.70±23.07	-13.83±38.44	-3.86±23.32
Ratio $R^2>0.9$	0.67	0.68	0.37	0.76

Reference:[1]H. Ding, ISMRM, 2011.[2] M. Lustig *MRM*, 2010. [3]M. Akçakaya, *MRM*, 2011. [4] C. A. McKenzie *MRM*, 2002.