## Accelerating parameter mapping with a locally low rank constraint

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**Purpose:** MR parameter mapping (PM) can provide intrinsic tissue information to detect pathological changes. However, PM is usually limited by lengthy scan time. To accelerate PM acquisition, compressed sensing with a low rank constraint (also known as partial separability) has been recently  $proposed^{[1,2]}$ . The low rank constraint can be further promoted in a local image region. A locally low-rank method (LLR)<sup>[3]</sup> has been studied in the context of cardiac dynamic imaging. In this work, the LLR method is used to accelerate PM and improve the accuracy and precision of the reconstruction.

<u>Methods</u>: In PM, a series of images is acquired with different acquisition parameters (*e.g.*, TI, TE, TR). Signal change in each image pixel is characterized by the parameter (T1, T2, etc) to be estimated and usually yields a smooth curve. A PM image series is generally low-rank<sup>[11]</sup> (global low rank, GLR) along the parametric dimension: PM images can be reformatted into a Casorati matrix, where each column in the matrix representing a single image with one acquisition parameter. PM image series are even more rank-deficient when partitioned into small blocks<sup>[3]</sup>, also called locally low rank. Define  $x_p$  as a matrix of the image with acquisition parameter p,  $y_p$  as a matrix of the acquired *k*-space data with acquisition parameter p,  $x_a$  as a matrix of all P images with all different parameters p,  $x_b$  as a submatrix of x in block b (where x is partitioned into small blocks), F as the Fourier transform operator,  $D_p$  as the under-sampling matrix with parameter p, and C as an operator that reformats  $x_b$  into its Casorati matrix. The LLR method can be formulated as:

## minimize<sub>x</sub> $\Sigma_b //Cx_b //*$ , subject to: $D_p Fx_p = y_p, p = 1, 2, ..., P$

where  $||x||_*$  is the nuclear norm of matrix x. A projection onto convex sets (POCS) method can be used to solve this problem<sup>[3]</sup>.

Results: LLR method was applied in two PM cases: (1) T1 mapping with a spin-echo inversion recovery sequence (IR-T1) and (2) T2 mapping with a multiple-echo spin-echo (MESE) sequence. In the IR-T1 experiment, a multi-compartment doped water phantom was scanned in a 7T scanner (GE MR950) with 16 different inversion times (TI) geometrically distributed from 50 to 2500ms. The dataset was retrospectively under-sampled by a factor of 4 in two scenarios: (a) 4 TIs with approximately geometric distribution between 50 and 2500ms were chosen from the original 16 inversions; (b) all TIs undersampled by a factor of 4, and reconstructed with the GLR and LLR methods. T1 estimation<sup>[4]</sup> was performed in the original dataset with 16 TIs and in scenarios (a) and (b). The results (Fig.1) showed that LLR had the smallest normalized root mean square error (nRMSE) and was most accurate across the T1 range.

In MESE T2 mapping, a brain scan with 32 echoes (TEs = 10-320ms, echo spacing = 10ms) was done on a 1.5T scanner (Siemens Sonata). The dataset was retrospectively undersampled by factors of 2 and 3, and reconstructed with the GLR and LLR method. The T2 mapping results are shown in Fig. 2. LLR

had less error (smaller nRMSE) than GLR with both acceleration factors. Notably, LLR was more accurate at tissue boundaries where white matter and gray matter and CSF can be mixed.

**Discussion & Conclusion:** In this work, the LLR method is applied to MR PM. Inversion recovery T1 mapping and multi-echo T2 mapping have been studied as examples. Compared to GLR, LLR can achieve better accuracy and precision. Image sparsity can be added as an additional constraint: the objective function becomes into  $(||\Psi x||_1 + \Sigma_b/|Cx_b/|_*)$ , where  $\Psi$  is a sparsifying transform (*e.g.*, wavelet transform).

**<u>References:</u>** [1] Doneva M, *et al.* Magn Reson Med 2010; 64:1114-1120; [2] Zhao B, *et al.* ISMRM 2012, p2233; [3] Trzasko J, *et al.* ISMRM 2011, p4371; [4] Barral J, *et al.* Magn Reson Med 2010; 64:1057-1067.



**Fig.2** Top: T2 measurement of the fully-sampled data, global low rank and locally low rank reconstruction with R = 2 and R = 3. Bottom: the corresponding T2 difference maps compared to fully-sampled data. Locally low rank produces less error, especially in boundary areas that are close to CSF (near ventricles and in cortex).