k-t Group Sparse Reconstruction Method for Dynamic Compressed MRI

M. Usman[1], C. Prieto[1], T. Schaeffter[1], and P. Batchelor[1]
[1]King's College London, London, United Kingdom

Introduction: Up to now, besides sparsity, the standard compressed sensing methods used in MR do not exploit any other prior information about the underlying signal. In general, the MR data in its sparse representation always exhibits some structure. As an example, for dynamic cardiac MR data, the signal support in its sparse representation (x-f space) is always in compact form [1]. In this work, exploiting the structural properties of sparse representation, we propose a new formulation titled 'k-t group sparse compressed sensing'. This formulation introduces a constraint that forces a group structure in sparse representation of the reconstructed signal. The k-t group sparse reconstruction achieves much higher temporal and spatial resolution than the standard l_1 method at high acceleration factors (9-fold acceleration).

Method: Our proposed method consists of two steps; group assignment and signal recovery. The signal support in x-f space is assumed to be known a priori. In group assignment step, based on the prior knowledge of signal support we assign elements in x-f space to distinct groups. A simple illustration of group assignment step is shown in Fig.1. The group assignment is done by running the modified run-length encoding (RLE) scheme [2] on signal support elements. This scheme assigns those support elements to a single group that are adjacent to each other in x-f space [Fig.1(c)]. Each of the elements in x-f space that are not part of signal support is assigned as a single element group. Once the groups are assigned to all elements in x-f space, we recover the signal in x-f space by 'k-t group sparse' reconstruction. The proposed reconstruction method recovers the signal by minimizing the number of non-sparse groups in x-f space, subject to the data constraints [3]. The formulation is as follows:

Let $\mathbf{X}$ be the signal in x-f space whose elements $\mathbf{X}_i$ {i=1, 2,.., N} after the group assignment step are assigned to K distinct groups $\{g_1, g_2, .., g_K\}$ which are non-overlapping and whose union gives the signal $\mathbf{X}$. The k-t group sparse formulation is given as:

$\min_{\mathbf{X}} \|\mathbf{X}^g\|_{1,2}$ subject to $\mathbf{AX=b}$, where $\|\mathbf{X}^g\|_{1,2}$ is the mixed l_1-l_2 norm given as $\|\mathbf{X}^g\|_{1,2} = \|\mathbf{X}^g_1\|_2+\|\mathbf{X}^g_2\|_2+\ldots\ldots+\|\mathbf{X}^g_K\|_2$, $\|\mathbf{X}^g_j\|_2$ being the l_2 norm of the vector containing all elements in x-f space assigned to the group $\{g_j\}$, $\mathbf{A}$ is the measurement matrix, $\mathbf{b}$ is the set of measurements in k-t space. The summation over l_2 norms enforces sparsity in selection of groups. The proposed method was tested on retrospective cardiac gated CINE data of 50 cardiac phases acquired on Philips MRI scanner 1.5T, SSFP sequence, FOV 350x350 mm^2, acquisition matrix size (224x155x50). The data was simulated by randomly under-sampling in k-t space. For true x-f space signal support, a threshold above the noise level was set in fully-sampled x-f space and all elements having intensities above the threshold were assigned to be the part of signal support. In addition to using true signal support for k-t group sparse reconstruction, we also used training data for signal support estimation. The training data was simulated by using 10 central k-space lines (6.4% of fully sampled k-space). A threshold above the noise level was empirically set in x-f space of l_2-reconstructed training data and elements having intensities above the threshold were assigned to be the part of signal support. We compared k-t group sparse method results with standard l_1 method. Our reconstructions were based on SPGL1 l_1 minimization code [4].

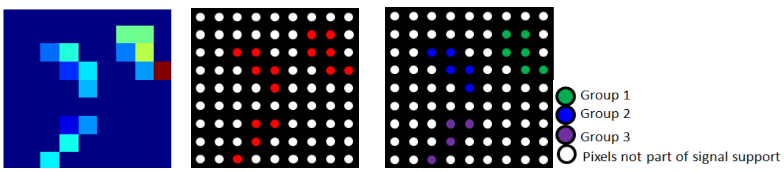

Fig. 1: Illustration of group assignment step in k-t group sparse technique: (a) 9x9 sparse image (b) its signal support, red dots show the signal support elements c) Groups formed based on modified RLE

Results: The x-f space reconstruction for different methods with 9-fold acceleration is shown in Fig.2. The l_1 reconstruction [Fig.2(b)] failed to reconstruct many signal components in dynamic region of x-f space. Using true x-f signal support (from fully sampled data), the groups formed in x-f space by RLE scheme are shown in Fig.2(c).

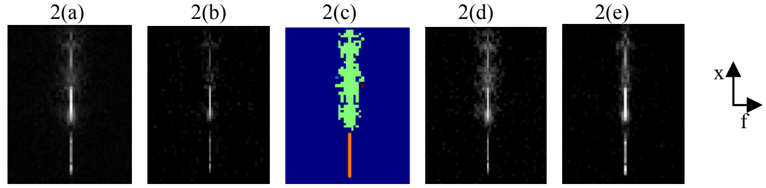

Fig.2: x-f space reconstruction (9-fold acceleration): (a) fully-sampled x-f space (b) l_1 reconstruction (c) Four groups (shown in different colors) formed from true x-f support by RLE scheme, elements not part of signal support are shown as dark blue background ;(d) k-t group sparse reconstruction using true x-f support (GS) (e) k-t group sparse reconstruction using x-f support from training scan (GS-training)

Each element in x-f space not part of signal support (shown as dark blue background in [Fig.2(c)]) was assigned as a single element group. Using the k-t group sparse constrained reconstruction, the x-f space reconstruction was nearly exact [Fig.2(d)]. Also, using x-f signal support from training scan, the proposed method was able to recover more non-sparse signal components in x-f space than l_1 method [Fig.2(e)].
The reconstructed cardiac frames (frame number 2 of 50-frame sequence) and temporal profiles corresponding to a dynamic region in FOV are shown in Fig.3. The standard l_1 reconstruction exhibits significant artefacts and fails to follow the variation in temporal profile (from diastole to systole). Using the actual x-f support or x-f support from the training scan, k-t group sparse method was able to reconstruct images with better quality and temporal fidelity. The RMS error variation as a function of acceleration factor is also shown in [Fig.3: bottom].

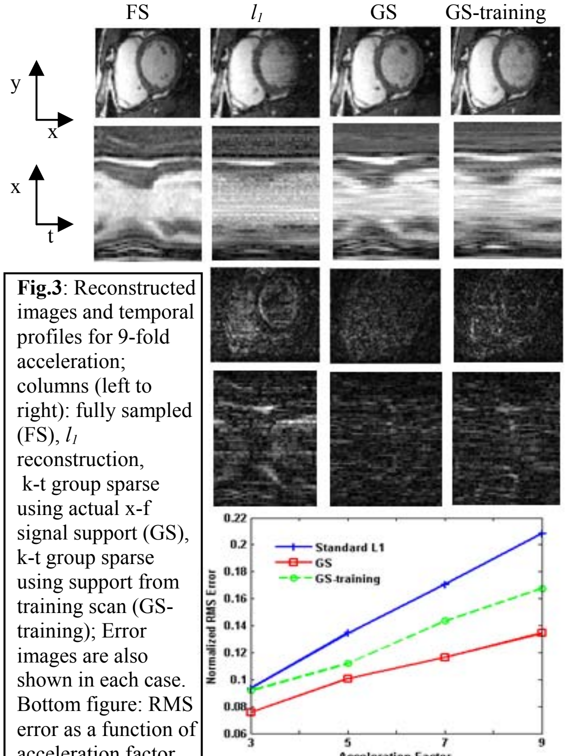

Fig.3: Reconstructed images and temporal profiles for 9-fold acceleration; columns (left to right): fully sampled (FS), l_1 reconstruction, k-t group sparse using actual x-f signal support (GS), k-t group sparse using support from training scan (GS-training); Error images are also shown in each case. Bottom figure: RMS error as a function of acceleration factor

Discussion: By enforcing x-f space signal support components to be in the form of groups, k-t group sparse offers very high temporal resolution compared to the standard l_1 method. The performance of k-t group sparse reconstruction depends on accuracy of the x-f space signal support which in turn depends on the threshold set in x-f space to detect signal support elements. A threshold much below the noise level in x-f space would result in noise components being detected as part of signal support. In group assignment step, this wrong detection would lead to signal and noise components being in the same group which deteriorates the k-t group sparse reconstruction. A threshold much higher than the noise level in x-f space would result in inefficiency of the algorithm since many true signal support components will be assigned as single element groups. The main limitation of our method is the requirement of a priori knowledge of signal support in x-f space which requires an additional training scan. In future, we will exploit the accuracy of x-f support model estimated from actual training data obtained at different spatial and temporal resolutions. Furthermore, without using additional training data, signal support estimation from interleaved training data will be evaluated. Also, instead of using simple thresholds for support detection in x-f space, advanced signal support model techniques such as x-f choice [5] can be used.

Conclusion: A novel reconstruction method was proposed to achieve high acceleration factors in dynamic compressed MRI. Using the x-f signal support as prior information, the proposed method achieved better reconstruction quality and temporal fidelity than the existing methods.

References: [1] S. Kozerke et al, MRM, 52:19–26, 2004 [2] R. Haralik et al, Computer and Robot vision, Addison-Wesley Publishing, 1992 [3] M. Usman et al, proc. ESMRMB, vol. 26, pp 368, 2009 [4] E. Berg, http://www.cs.ubc.ca/labs/scl/spgl1 [5] S. Malik et al, MRM, vol.56, p. 811-823, 2006