

K-T GROUP SPARSE USING INTENSITY BASED CLUSTERING

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INTRODUCTION: Over the last years, Compressed Sensing has been of great interest to accelerate dynamic MRI [1-4]. The recently introduced k-t Group Sparse (k-t GS) method [4] exploits not just the sparsity of dynamic MRI but also the spatial group structure of its sparse representation (x-f space). The reconstruction is done by solving a mixed L_1 - L_2 norm minimization that enforces sparsity in the group selection. K-t GS achieves higher acceleration factors compared to the conventional k-t Sparse method [1-2]. However, it presents two drawbacks: a) an additional training scan is required to assign the groups in x-f space, and b) the group assignment is based only on the connectivity of neighbouring pixels using a time consuming hard thresholding scheme. In this work we propose to modify k-t GS by using the sorted intensity of the sparse representation, estimated from the same acquired data, for group assignment. With this approach groups are assigned by clustering the expected intensity distribution of the x-f space and not the spatial structure of the x-f space as in k-t GS. We have called this approach k-t Group Sparse using Intensity based clustering (k-t GSI) and it has been tested in cine and perfusion cardiac images.

METHODS: a) *Prior information estimation:* is performed using a lattice-random undersampling pattern. A small central portion of k-space is acquired with a low undersampling factor (e.g. 2) using a lattice pattern, whereas the outer part is randomly sampled with a higher acceleration factor. The lattice-acquired data is used to reconstruct a low-resolution image by using sliding window (SW) reconstruction (Fig.1a-b).

b) *Group assignment:* The pixels of the estimated x-f space (Fig.1b) are assigned to N clusters according to their intensity values, using a K-means clustering algorithm. Clusters are sorted according to the mean intensity of their elements, with the cluster associated to the lowest intensities (N^{th}) being split in N_S single-element groups (background in Fig.1c). Splitting the N^{th} cluster into N_S single-element groups ensures that the groups formed from low intensity and noisy elements have the L_2 -norms not higher than the L_2 -norms of non-single element groups formed from higher intensity pixels. This produces a quasi-monotonically decrease of the L_2 -norm of the groups (Fig.1d). The assumption is that this behavior facilitates the sparse selection of the groups (L_1 minimization over the L_2 -norm of the groups, as shown in equations below). N is a global parameter that must be specified previous reconstruction.

c) *K-t Group Sparse reconstruction:* Let ρ be the x-f space of the reconstructed image and $\|\rho^g\|_2$ the L_2 -norm of the vector containing all elements of ρ assigned to the group g_j . K-t GSI is given by: $\text{Min } \|\rho\|_{1,2}$ s.t. $F_u \rho = B$, where F_u is the undersampled encoding matrix, B is the acquired data and $\|\rho\|_{1,2} = \|\rho^1\|_2 + \|\rho^2\|_2 + \dots + \|\rho^N\|_2$ is the mixed L_1 - L_2 norm of ρ .

d) *In-vivo experiments:* The proposed approach was tested in cine and perfusion cardiac images acquired on a 3T Philips scanner (B-FFE, 272mm^2 FOV, 256^2 matrix size, 40 cardiac phases). Raw data was undersampled retrospectively with effective acceleration factors (Q) up to 5 and 9 for the perfusion and cine data. Images were reconstructed using the proposed method and k-t Sparse reconstruction [1,2] with an iterative gradient-projection approach [5]. A lattice-random pattern was considered for k-t GSI reconstruction with 8% lattice sampling; since the same pattern produces poor results with the k-t Sparse method, a uniform random sampling was considered in this case. $N = 7$ was considered for the cine and perfusion reconstructions. The quality of the k-t GSI (in terms of root mean square error, RMSE) as function of the number of non-single element groups ($N_{NS} = N - 1$) was also studied.

RESULTS: Reconstruction results for $Q = 9$ are shown in Fig.2 for a particular cardiac phase of the cine sequence, and in Fig.3 for the perfusion data with $Q = 5$. In all cases the proposed method outperformed k-t Sparse reconstruction, resolving most of the aliasing and introducing less temporal blurring. The RMS error as a function of the number of N_{NS} for a particular frequency-encode line of the cine sequence is shown in Fig.4 for $Q = 7$ and 9. An optimal number of N_{NS} was observed for each Q, being in the same range (5 to 10) for different Q and for both the cine and perfusion data. In comparison with k-t GS that uses a different threshold value for the group assignment of each frequency encode, here N_{NS} is a global parameter for the reconstruction and does not need to be specified for each frequency encode.

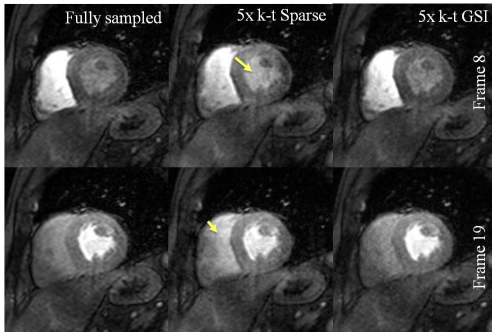


Fig3: Perfusion images at two different phases. K-t GSI (RMSE 0.27) and k-t Sparse (RMSE 0.58) reconstructions with $Q = 5$, in comparison with the fully sampled image.

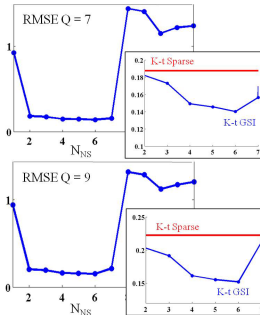


Fig4: RMSE of k-t GSI for $Q = 7$ and 9. Enlarged view for $N_{NS} = 2$ to 7 and compared with the k-t Sparse RMSE.

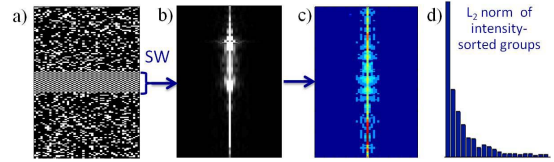


Fig1: a) Lattice-random sampling, b) x-f space of low-resolution image reconstructed from the lattice acquired data, c) intensity based clusters sorted according to their mean intensity, with the lowest intensity cluster (background) split in single-element groups, d) L_2 norm of intensity-sorted groups.

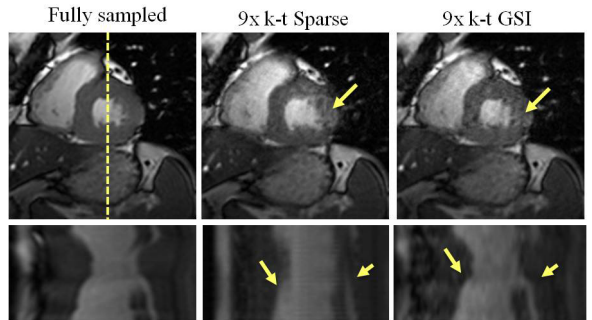


Fig2: K-t GSI (RMSE 0.91) and k-t Sparse (RMSE 1.1) reconstructions with $Q = 9$, in comparison with the fully sampled image. Corresponding temporal profiles (position indicated by yellow line) are also included (bottom). Temporal blurring and residual artefacts are observed with k-t Sparse, improved reconstruction is achieved with k-t GSI (arrows).

REFERENCES: [1] Lustig et al, MRM 2007, [2] Gamper et al, MRM 2008, [3] Otazo et al, MRM 2010, [4] Usman et al, ISMRM 2010 [4] van den Berg et al, SIAM 2008.