Cardiovascular MRI Reconstruction with Data-Driven Sparsifying Transform

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Introduction: Dynamic cardiovascular MRI facilitates the assessment of the structure and function of the cardiovascular system. One of the challenges in dynamic MRI is the prolonged data acquisition time. In order to fit the data acquisition time inside the motion cycles of the imaging subject, the data must be highly undersampled. Compressed sensing or sparsity-based MR reconstruction [1] takes advantage of the fact that the image is compressible in some transform domain, and enables reconstruction based on under-sampled *k*-space data thereby reducing the acquisition time. The design of such transform is a key to the success of the reconstruction. In this paper, we propose to use tight frame learning for computing data-driven transforms. Empirical results demonstrate improvement over the transform associated with the redundant Haar Wavelets.

Methods: Our proposed approach comprises of the following steps: 1) Acquire training images using similar acquisition protocols for dynamic cardiac imaging or generate a reference image from the acquired data itself. 2) Learn a tight frame from the reference or training images. 3) Perform the sparsity enforcing reconstruction using the learnt tight frame in an analysis formulation. In the remainder of this abstract we shall focus on generating a reference image from the acquired data itself.

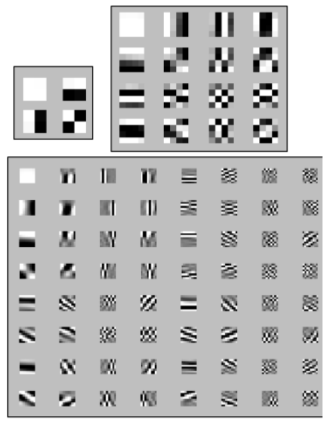

Figure 2 Learnt filters (top left 2×2, top right 4×4, bottom 8×8).

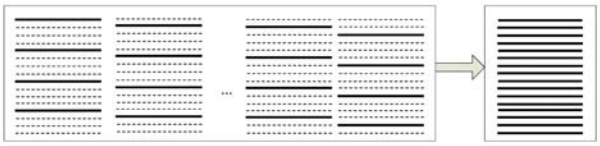

Figure 1 Generating mean (fully sampled) k-space data. In this example, the k-space is sampled every 4 lines. Acquired data are in solid lines, and missing data are in dashed lines.

<u>*Reference Generation*</u>: To acquire the cardiac images, the *k*-space data are under-sampled in an interleaved way, as shown in Figure 1, where each plot illustrates the sampled *k*-space for a given time point (acquired data in solid lines, and missing data in dashed lines). We propose to take the average in the temporal direction to generate the mean (fully sampled) *k*-space, as shown in rightmost plot of Figure 1(a). We generate the reference image by going from *k*-space to the image space.

<u>*Tight Frame Learning*</u>: With the reference image, we can construct an adaptive discrete tight frame to form the appropriate transform *W* using the algorithm described in [2]. The basic idea of the algorithm is as follows. Let $x^{ref} \in R^{N_x N_y}$ be the 1D vector from concatenating all columns of g^{ref}(the reference image) vertically together. The construction of the tight frame operator *W* is achieved by solving the following minimization.

$$\min_{u,\{f_i\}_{i=1}^{s}} \|u - W(f_1, f_2, \dots, f_s)x^{ref}\|_2^2 + \beta^2\|u\|_0, \qquad \text{subject to } W^TW = I \qquad (1)$$

The two unknowns are u which is the coefficient vector that sparsely approximates the canonical tight frame coefficient Wx^{ref} and $\{f_i\}_{i=1}^{s}$ which is the set of filters that generates a tight frame. The algorithm iteratively solves for the two unknowns by breaking the minimization into two minimizations over the two unknowns.

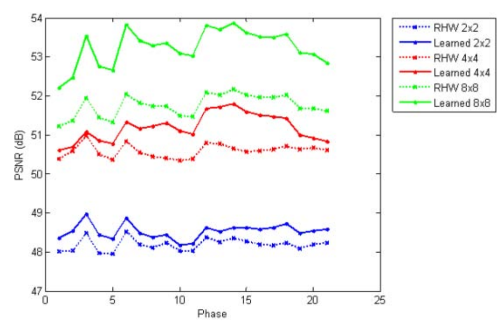

Figure 3 PSNR of the cardiac MR reconstruction compared to the ground truth.

<u>*Image Reconstruction*</u>: One of the compressed sensing types of image reconstruction for parallel MRI consider the following problem [3].

$$\min_x \frac{1}{2}\sum_{i=1}^{N_c}\|F_u(c_i \odot x) - y\|_2^2 + \lambda\|Wx\|_1 \qquad (2)$$

In this representation, *x* is a 1D vector which is the vectorized (concatenating columns vertically together) version of the signal to be reconstructed. For dynamic imaging, the signal to be reconstructed is 3D if the data is a time sequence of 2D images, or 4D if the data is a time sequence of 3D images. N_c is the number of coils. F_u is the operator for image acquisition which includes Fourier transform and undersampling in *k*-space. c_i is the coil sensitivity profile for the i^{th} coil, and y is the acquired *k*-space data written in the vectorized form. The regularization term is the l_1-norm of the signal in the transform domain, where *W* represents the transform. In this work, we are going to compare reconstruction results using the transform learned in Eq. (1) against the transform associated with the redundant Haar wavelet.

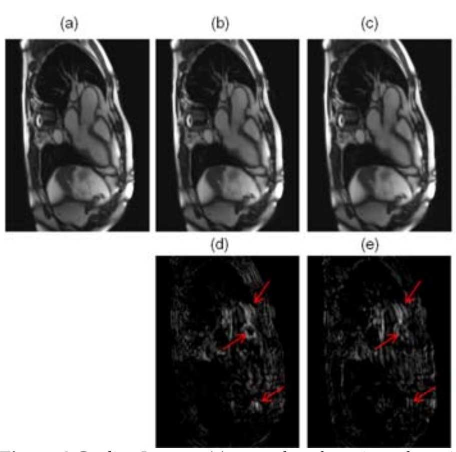

Figure 4 Cardiac Images: (a) ground truth at time phase 1; (b) reconstruction from 8x8 size redundant Haar wavelet transform of under-sampled data at time phase 1; (c) reconstruction from 8x8 size learnt transform of under-sampled data at time phase 1; (d) difference image of (a) and (b); (e) difference image of (a) and (c).

<u>Data</u>: The algorithm is validated on clinical cardiac data with 2D in spatial and 1D in time acquired from healthy volunteer on a 1.5T clinical MR scanner (MAGNETOM Aera, Siemens Healthcare, Erlangen, Germany). In order to measure the performance, we initiate from a set of undersampled data with acceleration factor of *R*=2. We take the reconstruction results from this data as the ground truth and simulate the test data with acceleration factor *R*=6 by downsampling the *k*-space data by 3 times. The data size is 192 pixels by 144 pixels with 30 coils and 21 time phases.

Results: The reconstruction results are compared with the ground truth by computing the PSNR (Peak Signal-to-Noise-Ratio). Figure 2 shows the learnt filters of sizes 2 pixels by 2 pixels, 4 pixels by 4 pixels and 8 pixels by 8 pixels. Each little square shows one vector in the set of learnt tight frames $\{f_i\}_{i=1}^{s}$ in the matrix form. The texture of the cardiac images is captured well in the learnt filters. Figure 3 shows the PSNR of different filter sizes and with different sparsity transforms at each of the 21 time phases. From this figure, we see that the learnt transform outperforms the transform associated with the redundant Haar in terms of PSNR. Also, larger filter sizes result in higher PSNR. Examples of the reconstructed images are shown in Figure 4. The learnt transform leads to less difference shown in the marked regions of the difference image.

Discussion and Conclusion: We designed a new image reconstruction process for dynamic MRI by first obtaining a reference image, learning a tight frame from the reference image and applying the learnt operator to the reconstruction. The approach is effective in reconstructing images with complex anatomical structure and texture. By comparing the learnt operator against the redundant Haar operator, the learnt operator leads to higher PSNR and less image artifacts.

Disclaimer: The concepts and information presented in this paper are based on research and are not commercially available.

References: [1] M. Lustig et al., Magnetic Resonance in Medicine, 2007. [2] J. –F. Cai, et al., Preprint submitted to Elsevier, 2012. [3] J. Liu et al., Proc Intl Soc Mag Reson Med, #4249, 2012.