Dynamic Parallel-Imaging Reconstruction with Image-Block Dictionaries

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TARGET AUDIENCE – This work is targeted to an audience interested in dynamic Parallel Imaging (PI) and Compressed Sensing (CS), and more specifically interested in dictionary-based reconstruction. The presented results are of interest to researchers involved in cardiac imaging.

PURPOSE – Adaptive dictionary-based regularization methods such as partially separable functions[1], or adaptive dictionary learning[2,3], are powerful sparsifying transforms which can achieve significant noise reduction in Compressed Sensing reconstructions[4]. When using these methods, complex, iterative computations must be performed on both the dictionary and the sparse representation of the target image with the dictionary atoms, for example using the k-SVD algorithm[5]. This work aims to demonstrate that by relying on coil sensitivity information rather than sparsity constraints, an image-domain block dictionary from a calibration dataset can produce accurate reconstructions of highly accelerated dynamic MR experiments, with very light computational load. As such, the proposed method can be viewed as a new combined Parallel Imaging and Compressed Sensing reconstruction technique.

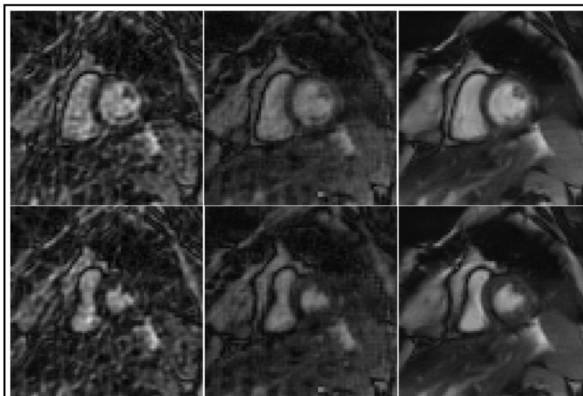

Figure 1. Undersampled images (left) compared to CG-SENSE reconstructed images (middle) and proposed method (right) at diastolic end (top) and systolic end (bottom)

METHODS – The reconstruction scheme is demonstrated for a radial dynamic cardiac acquisition, where N_t fully-sampled images are acquired during a free-breathing, non-gated calibration phase. The N_t images are assembled in a training-set D. An aliasing operator φ corresponding to the acquisition scheme is applied to each entry of D with density compensation, yielding an aliased dictionary D_φ. For a given time frame, the reconstructed image is recovered by performing the following operations at each aliased pixel location i:

Step 1 - A block B_i of dimension $N_{coils}\times N_y\times N_x$ centered on location i is extracted from the undersampled, density compensated frame **y**, yielding a local aliased image y_i.

Step 2 - The same block is extracted from each entry of D_φ, yielding a local aliased dictionary $D_{\varphi,i}$

Step 3 - The following equation is solved:

$$\boldsymbol{\rho}_{r,i} = \mathbf{D}.\mathbf{m}_i \quad s.t. \quad \mathbf{m}_i = \arg\min_{\mathbf{m}} \left\| \mathbf{y}_i - \mathbf{D}_{\Phi,i}.\mathbf{m} \right\|_2 \qquad [1]$$

The resulting object $\rho_{r,i}$ is an unaliased multi-channel image, with identical coil sensitivity information as the target image. If $N_t \approx N_{coil}N_yN_x$ or if the atoms of D_φ are highly correlated to y_i , then [1] is well posed and $\rho_{r,i}$ is in close agreement with the latter after aliasing. Since $\rho_{r,i}$ both respects coil sensitivity fidelity and data fidelity conditions, $\rho_{r,i}$ is close to the target image within the block B_i, provided the point spread function of φ is such that most of the energy of y_i comes from target pixels within B_i (the conventional assumption in compressed sensing). After setting $\rho_{r,i}$ to 0 outside of B_i, the final reconstructed image ρ_r is an average of all the $\rho_{r,i}$:

$$\boldsymbol{\rho}_r = \sum_i \frac{\boldsymbol{\rho}_{r,i}}{N_y N_x} \qquad [2]$$

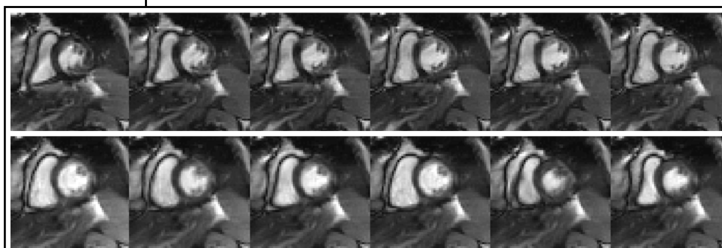

Figure 2. Sample frames from the calibration data (top), compared to sample reconstructed frames (bottom).

To test the validity of such a reconstruction, a dynamic cardiac imaging experiment was conducted with a total of 4 subjects with high ejection fraction, scanned on a 1.5T Avanto or 1.5T Espree scanner (Siemens Medical Solutions, Erlangen, Germany) using a combined spine and abdominal receiver array with 12 to 15 channels, with a radial bSSFP sequence (TR=2.64ms, resolution=2.3x2.3mm, slice thickness=6-8mm). For each subject, 26 calibration frames were acquired, with no ECG gating or breath-holding, then 60 consecutive frames were acquired with an acceleration factor R=8 (16 projections for 128x128 matrix) so that the temporal resolution for real-time imaging was 42.2 ms per image. Each frame was reconstructed offline using the proposed method, with blocks of size 5x5, using Matlab R2010a with 2.0GHz Intel Xeon CPU and 32 GB RAM and the NUFFT Toolbox provided by Jeffrey Fessler[6]. Additionally, a coil sensitivity map was extracted from the averaged calibration phases images using the adaptive method[7], and the undersampled images were reconstructed with the CG-SENSE method[8] for comparison.

RESULTS – Figure 1 shows a reconstructed end systolic and end diastolic frame for a sample subject, along with their respective aliased frames. Our block-wise approach provides a clear increase in image quality compared to either the undersampled or CG-SENSE reconstruction. In order to evaluate any reconstruction bias introduced by the calibration frames, calibration frames are compared with the , reconstructed frames at various time-points in figure 2. Even though the cardiac motion is averaged out in the long calibration frames (time=380ms), the real-time images (time=42.2ms) reconstructed with the block-wise approach properly represent the cardiac motion. The total computation of all dictionaries $D_{\varphi,i}$ was performed under 27 seconds. The reconstruction of a given frame required on average 37 seconds.

DISCUSSION – Here we have shown a novel combination of dictionary based compressed sensing and parallel imaging for use in real-time cardiac imaging. The computational load of the proposed technique is light and results in acceptable reconstruction time with simple CPU computing. Unlike CG-SENSE, no explicit computation of the coil maps is needed, as the sensitivity information is exploited implicitly via the block dictionaries. Also the technique does not require that the calibration phase images be acquired with the same trajectory scheme as the undersampled frames.

CONCLUSION – In addition to sparsifying transforms in Compressed Sensing, image-block dictionaries can be used to exploit embedded coil-sensitivity and feature information to perform Parallel Imaging type reconstructions. Such reconstructions are computationally light, with acceptable image quality at high acceleration rates.

References: 1. Liang Z-P, IEEE 2007; **2.** Ravishankar S, et al. IEEE transactions on medical imaging 2011; **3.** Lingala SG, et al. ISMRM 2012; **4.** Lustig M, et al. MRM 2007; 5. Aharon M, et al. IEEE transactions on signal processing 2006; **6.** http://web.eecs.umich.edu/~fessler/code/; **7.** Walsh DO et al. MRM 2000; **8.** Pruessman et al. MRM 2001.

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