Compressed Sensing using Prior Rank, Intensity and Sparsity Model (PRISM): Applications in Cardiac Cine MRI

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Introduction: Compressed sensing (CS) has recently been applied to MR image reconstruction to shorten data acquisition time[1,2]. In this work, we propose a novel CS method for dynamic MRI applications using Prior Rank, Intensity and Sparsity Model (PRISM) [3,4] and evaluate this technique for cardiac cine MRI.

Theory: A dynamic MR image is represented by a matrix X, where all the pixel values for a given temporal frame are in a column vector. *X* can be decomposed into a background component X_L that does not change over time, and a changing residual X_S, hence $X = X_L + X_S$. Let Y be the incoherently (randomly) under-sampled k-space data and let A be Fourier transform from image space to k-space (temporal direction is not transformed). Then PRISM reconstruction is formulated as the following optimization problem: $(X_L, X_S) = \underset{(X_L,X_S)}{\arg\min} \|AX_L + AX_S - Y\|_2^2 + \lambda_* \|X_L\|_* + \lambda_1 \|WX_S\|_1 + \lambda_2 \|WX\|_*$, where the first term $\|AX_L + AX_S - Y\|_2^2$ is the data fidelity term, $\|\cdot\|_*$ denotes the nuclear norm (sum of singular values), $\|\cdot\|_1$ denotes L1 norm, and W is a sparsifying transform. In this work, we use tight framelet transform (TF)[5,6] for W, although the commonly used wavelet transform can also be used. The optimization is iteratively solved by the Split Bregman method. Two key novel approaches are used in PRISM to improve image quality and enable higher acceleration rates. First, the stationary background, which is automatically calculated by minimizing its rank ($\lambda_* \|X_L\|_*$ term), complements the L1 minimization step of the CS reconstruction because this further sparsifies the residual image. Secondly, the sampling pattern in k-t space is made more incoherent by sampling a different set of k-space points for different temporal frames. Although similar approaches have been proposed recently[7,8], the combination of the above two approaches have not been thoroughly studied.

Methods and Materials: PRISM was tested on cardiac cine MRI data sets acquired on 6 healthy subjects. The data was fully sampled and retrospectively under-sampled at rates of 2X, 4X, 5X, 6X and 9X. The acceleration rates quoted in this abstract are true acceleration rates calculated by dividing total used k-space lines over total number of full k-space lines. As a comparison to PRISM reconstruction, a frame-by-frame CS reconstruction based on TF transform sparsity (TF-CS) was also performed on the retrospectively under-sampled data set. The PRISM and TF-CS reconstructions shared the same under-sampling pattern in k-t space. As another comparison, the same data sets were also retrospectively under-sampled in a regular pattern and reconstructed using GRAPPA. Accuracy of images reconstruction was evaluated measuring the blood-myocardium border sharpness along a profile drawn over the septum or the anterior wall[9]. The quality of the cine images was graded by 2 blinded evaluators using a 4 point scale (1=poor, 2=fair, 3=good, and 4=very good).

Results: At lower acceleration rates of 2X and 4X, PRISM is comparable to TF-CS (Fig. 1). Our data sets were acquired using 6 coils, and GRAPPA reconstruction started to show significant artifacts and SNR degradations at 4X. Contrast from reconstructed images is maintained at rate 4X and higher as sharpness scores decrease only from 1.64 ± 0.81 (1X) to 1.34 ± 0.68 (4X) for CS-TF and from 1.64 ± 0.81 (1X) to 1.31 ± 0.58 (4X) for PRISM. There was no significant difference of sharpness scores between PRISM and TF-CS. However image quality of PRISM was rated significantly higher than TF-CS at rates higher than 4X ($p<0.01$). As shown in Fig. 1, TF-CS reconstructions were "patchy" at rates higher than 5X. There was a complete agreement between our 2 blinded reviewers ($p>>0.05$). With references (fully sampled) images rated 3.80 ± 0.59 out of 4, TF-CS and PRISM scored as *good* (2.64 ± 0.49 and 3.07 ± 0.54 resp. for 4X) but difference between them was significant ($p=0.01$). Even at very high under-sampling rates PRISM scored as *fair* (20.4 ± 0.43 for 9X) when TF-CS is considered *poor* (1.14 ± 0.36 for 9X, $p<0.01$).

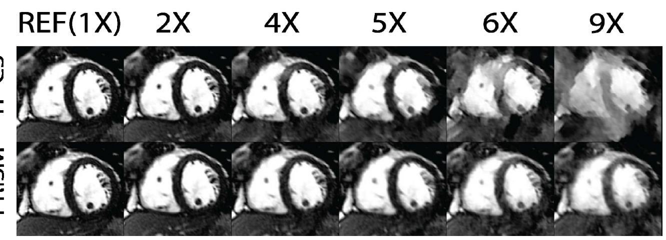

Figure 1: Reconstruction of a diastolic frame using tight-framelets CS (TF-CS) and PRISM at different acceleration rates.

Discussion and conclusion: The under-sampling pattern used in this work proves to be important for PRISM reconstruction, where multiple temporal frames are formulated in a single reconstruction problem. Traditional CS strategies, where the random k-space under-sampling pattern is the same between different temporal frames, result in more coherent artifacts and as a result the rank minimization term captures these coherent artifacts as a background component and excludes them from the L1 norm minimization term, which is undesirable. PRISM is a technique that differs from the previous CS techniques in the ability to apply the sparsifying transform (TF) after background suppression using rank minimization. However we show here that the under sampling pattern is required to be random in all dimensions, esp. time, for the rank minimization to avoid considering recurring artifacts as background. There is a legitimate concern on eddy-currents produced by highly under-sampled SSFP acquisitions. Acquiring paired lines has been proposed to reduce this impact[10]. Therefore we simulated under-sampling pattern using random paired lines and observed no significant differences in reconstructed image quality.

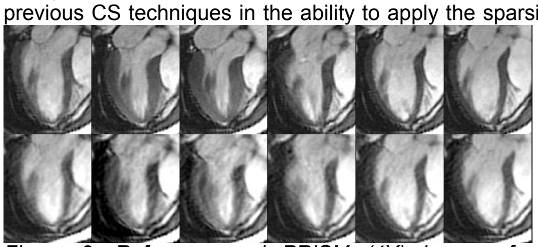

Figure 2: Reference and PRISM (4X) images for different phases of the cardiac cycle. PRISM images show little temporal blurring.

Results show dynamic 2D MRI could be greatly accelerated using PRISM (Fig. 2), providing cine MRI within only few heartbeats. Additional dimensions would enable even greater acceleration such that 3D dynamic contrast-enhanced MRI or Magnetic Resonance Angiography (MRA) could benefit from PRISM, where the underlying structure of the anatomy and blood vessels do not change, but only the signal intensity changes. However low-rank minimization parameters need optimization to avoid potential temporal blurring. Overall our Prior Rank, Intensity and Sparsity Model (PRISM) provides sharp and good-quality image series even from highly under-sampled k-space data when state-of-the art traditional compressed sensing fails to reconstruct quality images.

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