Accelerated Dynamic MRI Using Multicoil Low-Rank Matrix Completion

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INTRODUCTION: Compressed sensing enables accelerated acquisition of dynamic MRI data by exploiting spatial and temporal correlations to reconstruct undersampled k-space data [1]. Further accelerations can be achieved by combining compressed sensing and parallel imaging [2]. However, the combination of compressed sensing and parallel imaging requires the selection of an appropriate sparsifying transform and explicit coil calibration information. Low-rank matrix completion has recently been introduced as an alternative to compressed sensing reconstruction that does not require a specific sparsifying transform, but instead promotes low-rank structure by exploiting correlations in the undersampled data [3]. Low-rank matrix completion was also demonstrated to perform calibrationless parallel imaging reconstructions by exploiting local k-space correlations between coils [4]. In this work, low-rank matrix completion is proposed as a new generalized way to combine compressed sensing and parallel imaging for accelerated dynamic MRI acquisitions by jointly exploiting implicit temporal and coil correlations without an explicit sparsifying transform or coil calibration procedure.

THEORY: The requirements for low-rank matrix completion are (a) low-rank original matrix (sparsity) and (b) random undersampling of the original matrix (incoherence). Local k-space correlations between coils result in a low-rank matrix, when the columns of that matrix are formed by concatenating overlapping k-space blocks from all coils, as described in [4]. Further rank reduction can be obtained for dynamic MRI data by concatenating blocks corresponding to consecutive time frames in each column, which are highly correlated (Fig. 1). This matrix presents a Hankel structure (constant skew-diagonals, as shown by blue points in Fig. 1), which was demonstrated to improve the performance of matrix completion [4]. k-t incoherence conditions can be accomplished by using a different random undersampling pattern for each time point. Reconstruction of k-t undersampled data can be performed by completing missing entries in the multicoil k-t matrix which result in the lowest rank matrix.

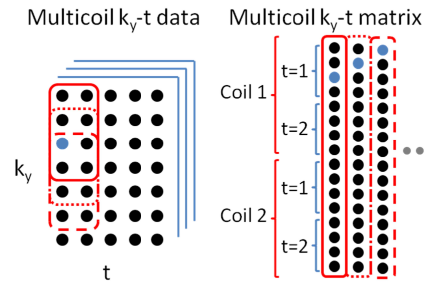

Fig. 1: Temporal and coil correlations can be exploited to obtain a low-rank matrix, when the columns are formed by concatenating small k-space blocks from consecutive time points and multiple coils. In the example, overlapping blocks of 4 k_y points and 2 time frames from all coils are concatenated to form each column, resulting in linearly dependent rows .

METHODS: 2D cardiac cine imaging was performed on a 3T Siemens Trio scanner using a standard 12-coil matrix body array. Fully-sampled data were acquired using a 256×256 matrix (FOV = 320×320 mm^2) and 24 temporal frames and retrospectively undersampled by a factor of 6 using a different variable-density random undersampling along k_y for each time point. The reconstruction process was performed separately for each fully-sampled k_x point to enable tractable SVD computations for each iteration and parallel computing implementation. Overlapping blocks of 10 k_y points and 4 temporal points were employed to create a 480×4940 multicoil k_y-t matrix for each k_x point. Low-rank matrix completion was performed using the iterative singular value thresholding algorithm [4-5], where at each iteration the missing k-space points are updated by truncating the singular value decomposition of the multicoil k_y-t matrix. The starting point for the reconstruction algorithm was the zero-filled k-space data and the stopping point was chosen to be when the estimated missing k-space points present a change of 0.5% or less. The algorithm converged between 26 and 35 iterations. The reconstruction was implemented using the parallel computing toolbox in Matlab. For comparison purposes, a k-t SPARSE-SENSE reconstruction was performed using temporal FFT as sparsifying transform and explicit coil calibration using the temporal average of the zero-filled k-space reconstruction as reference to compute the coil sensitivity maps [2].

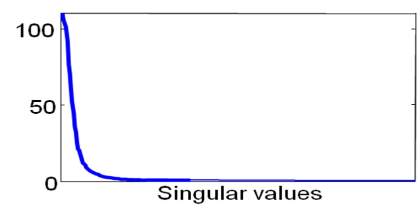

Fig. 2: Singular values of the k_y-t matrix for a representative k_x point of the cardiac cine data.

RESULTS: The fully-sampled k_y-t matrix for each k_x point presented about 10-fold decrease in rank, i.e. only 50 out of 480 singular values and vectors were required to represent the time series (Fig. 2 shows the singular values for a representative k_x point). Reconstruction of 6-fold undersampled cardiac cine data using low-rank matrix completion compared favorably to k-t SPARSE-SENSE reconstruction, particularly at systolic cardiac phases where the latter presented temporal blurring artifacts (Fig. 3). This is due in part to the better sparsification offered by exploiting intrinsic data correlations rather than trying to fit the data to an analytical sparsifying transform.

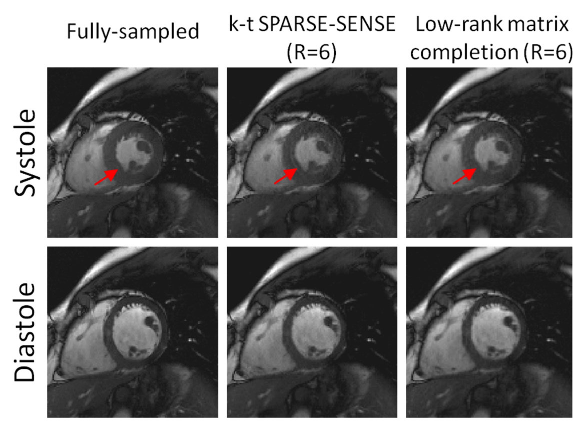

Fig. 3: Reconstruction of 6-fold undersampled data using k-t SPARSE-SENSE with temporal FFT and explicit coil calibration and low rank matrix completion with implicit k-t data sparsification and coil correlation. The red arrows indicate the location of temporal blurring artifacts in the k-t SPARSE-SENSE reconstruction for the systolic frame.

DISCUSSION: We demonstrated that implicit temporal and coil correlations can be exploited to accelerate dynamic MRI acquisitions without the need for an explicit sparsifying transform or coil calibration procedure. This reconstruction represents a generalized approach to the combination of compressed sensing and parallel imaging, where implicit data correlations are exploited rather than using analytical transforms and encoding models. Future work includes the use of fast SVD algorithms and implementation using GPUs to speed up image reconstruction.

REFERENCES: [1] Lustig M et al. MRM 2007; 58:1182-95. [2] Otazo R et al. Magn Reson Med. 2010;64(3):767-76. [3] Candes E et al. Found Comp Math 2008; 717-72. [4] Lustig M et al. ISMRM 2011; 483. [5] Cai F et al. SIAM J on Opt 2008; 1956-82. **GRANT SPONSOR:** NIH R01-EB000447.