k-t ISD: Dynamic Cardiac Imaging Using Compressed Sensing with Iterative Support Detection

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INTRODUCTION:

Most existing dynamic MRI methods using compressed sensing (CS) [1-3] only exploit the prior information that the dynamic image series is sparse after a certain transform. Other prior information about the unknown MR images is usually available and should also be exploited in CS reconstruction algorithms. In this abstract, we study how to obtain and exploit the knowledge on the support of sparse signals in dynamic imaging applications. We propose a new method, named *k-t* Iterative Support Detection (*k-t* ISD), to incorporate the additional information that the support in temporal-frequency domain (*x-f* space) is partially known in CS reconstruction. The support knowledge is obtained automatically by an iterative detection approach, and incorporated in reconstruction by excluding part of the signal at the known support from the cost function in the constrained minimization process. Improvement of *k-t* ISD over the basic CS approach is demonstrated using *in vivo* cardiac cine MR experiments.

THEORY AND METHOD:

Recent studies in CS theory have proved that CS with partially known support can reduce the required number of measurements for a given reconstruction quality or improve the reconstruction quality for a fixed number of measurements, compared to the basic CS [4-6]. In the proposed *k-t* ISD method, we assume the dynamic image $\boldsymbol{\rho}$ in *x-f* space is not only sparse, but its support (locations of nonzero elements) is also partially known. Defining the known support as T and the unknown one as Δ, the image in *x-f* domain can be reconstructed by solving a truncated ℓ_1 minimization problem: $\min\|\boldsymbol{\rho}_\Delta\|_1 \quad s.t. \|\mathbf{d}-\mathbf{F}\boldsymbol{\rho}\|_2 \le \varepsilon$ (1), where $\mathbf{d}$ is the acquired data in *k-t* space, $\boldsymbol{\rho}$ is the image series represented in *x-f* space, $\boldsymbol{\rho}_\Delta$ denotes the truncated $\boldsymbol{\rho}$ excluding the known support, $\mathbf{F}$ is the Fourier transform along the *k-t* direction, and ε is noise level. This formulation suggests that, in searching for a sparse solution to satisfy $\mathbf{F}\boldsymbol{\rho}=\mathbf{d}$, only a much smaller space excluding the known support T needs to be considered. In other words, truncated CS favors a solution with more zeros outside T given the prior information that the signal is non-zero inside T. However, the support information is usually difficult to obtain because $\boldsymbol{\rho}$ is unknown and its support is patient and scan dependent [7]. To avoid pre-scan [7] or empirical estimate [8], we propose to learn the support knowledge in *x-f* space from the reconstructions iteratively using an iterative support detection (ISD) algorithm [9]. Specifically, an initial reconstruction is performed using the basic CS method. We then learn the support in *x-f* space from the initial reconstruction by identifying the locations whose values are above a threshold. This support is considered known and used in truncated CS for an updated reconstruction. The detection using the latest reconstruction and reconstruction using the latest detected support is then repeated alternatively until convergence. In our implementation, we rewrite (1) as a weighted ℓ_1 minimization problem: $\min\|\mathbf{W}\boldsymbol{\rho}\|_1 \quad s.t. \|\mathbf{d}-\mathbf{F}\boldsymbol{\rho}\|_2 \le \varepsilon$ (2), where $\mathbf{W}$ is a diagonal weighting matrix whose diagonal value is 1 if the corresponding element in *x-f* space belongs to the unknown support Δ, or 0 otherwise. FOCUSS [10] algorithm was used to solve this weighted optimization problem. The threshold in ISD scheme is set as $\tau^l = \|\boldsymbol{\rho}^l\|_\infty \big/ \delta^l$ with $\delta^l = 8^{l+1}$, where $\boldsymbol{\rho}^l$ is the *l*-th *k-t* ISD intermediate reconstruction.

RESULTS AND DISCUSSION:

The data was acquired on a 3T Siemens scanner. The SSFP sequence was used with a flip angle of 44 degree and TE/TR = 1.5/3.0msec. The fully acquired *k-t* measurements have a size of 160×133×15×5 (#frequency encoding × #phase encoding × #frame × #coil). The FOV was 350mm × 262mm and the slice thickness was 7 mm. The heart rate was 54 bpm. The full *k*-space data were acquired and used as the reference. The variable-density random sampling pattern was generated to simulate a reduction factor of 3, with central 8 fully sampled phase encodings. The proposed *k-t* ISD, *k-t* FOCUSS [2], and two-step OMP [11] methods were used for reconstruction. Images of each coil were obtained separately and then combined using root sum-of-square (SoS). Since strict convergence is not observed in this application, we calculate the normalized difference between the adjacent iterations and then terminate iterations once the difference is below a threshold. Figure 1 shows the reconstructions, corresponding difference images and zoomed-in images at a single time frame. The number of iterations of support detection in *k-t* ISD is 2. As highlighted by arrowheads, *k-t* ISD presents fewer undersampling artifacts along the phase encoding direction than *k-t* FOCUSS and less noise than two-step OMP.

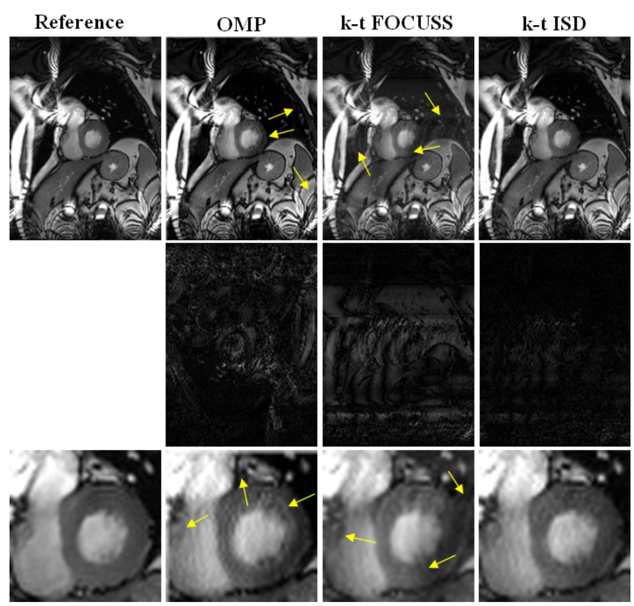

Figure 1: Reconstructions at a single frame using different methods, and their corresponding difference images and zoomed-in images with a reduction factor of R=3.

CONCLUSION:

A novel method, named *k-t* ISD, is proposed to accelerate the dynamic MRI using CS. The method iteratively learns and exploits the support knowledge in *x-f* space to improve CS reconstruction. The results show that the proposed method is able to suppress more artifacts and preserve more details of dynamic images than the existing CS methods do.

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