k-t CS-NLG: Dynamic Imaging Reconstruction with Compressed Sensing and Nonlinear GRAPPA

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INTRODUCTION:
Among the fast imaging techniques, parallel imaging [1,2] and compressed sensing [3] are two promising techniques that accelerate the acquisition speed through undersampling the k-space below the Nyquist rate. Parallel imaging uses the information that signals received from multiple coils have distinct spatial sensitivities to reconstruct the missing k-space data. Compressed sensing (CS) exploits the sparseness of the image in a certain domain to obtain the original image. Due to the complementary information used in these two techniques, it is of great interest to combine these two techniques. Several techniques [4-6] have been developed to combine pMRI and CS for static imaging. However, in dynamic imaging, the two techniques are simply combined by incorporating the coil sensitivities in the data consistence term based on the SENSE equation. It is difficult to maximize the accelerations with such a simple combination. In this abstract, a new dynamic MRI reconstruction scheme is proposed that combines the CS-based dynamic imaging method and parallel imaging technique more effectively. The method decouples the reconstruction process into two sequential steps. In the first step, a series of aliased dynamic images is reconstructed using a CS method from the highly undersampled k-space data. In the second step, the missing k-space data for the original image are reconstructed by the nonlinear GRAPPA technique [7]. We name the method *k-t* Compressed Sensing – NonLinear GRAPPA (*k-t* CS-NLG). The performance of the proposed method is evaluated using *in vivo* MR cardiac cine experiments.

THEORY AND METHOD:

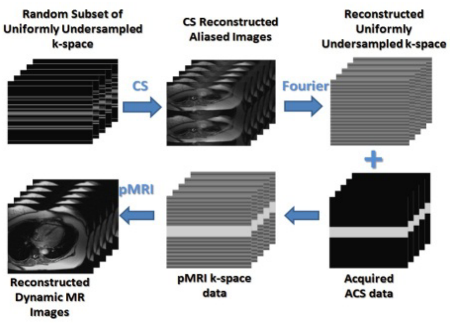

Fig.1. Proposed reconstruction procedure

In data acquisition, the *k-t* space is undersampled by taking a random subset of the uniformly undersampled k-space data at each time point. Extra auto calibration signals (ACS) are also acquired. The proposed method then reconstructs the dynamic MR images in two sequential steps. In the first step, we use CS to reconstruct a series of dynamic images that are aliased spatially, but not in time. These images correspond to sets of uniformly undersampled k-space data at different time points. The reconstruction is formulated as $\min\|\boldsymbol{\rho}_u\|_1 + \mathbf{TV}_{S-T}(\boldsymbol{\rho}_u)$ (1) where **F** denotes the two-dimensional Fourier transform along both *x-f* directions, $\boldsymbol{\rho}_u$ is the aliased image series in *x-f* domain to be reconstructed, operation $\mathbf{TV}_{S-T}(\cdot)$ denotes the total variation in the spatial-temporal (*x-t*) domain. Nonlinear conjugate gradient is used to solve this optimization problem. After finding $\boldsymbol{\rho}_u$ in *x-f* domain, a two dimensional Fourier transform is applied on $\boldsymbol{\rho}_u$ to generate the uniformly undersampled k-space data at different time points. In the second step, we exploit nonlinear GRAPPA to obtain all the data in the full k-space. Specifically, nonlinear GRAPPA uses a second-order polynomial (nonlinear) model to represent the relationship between the missing and acquired undersampled k-space data. Such a nonlinear model has been shown to suppress GRAPPA noise significantly. The use of nonlinear GRAPPA in the sequential method can reduce the error propagation from the first CS step. The flowchart of the reconstruction process is illustrated in Fig.1.

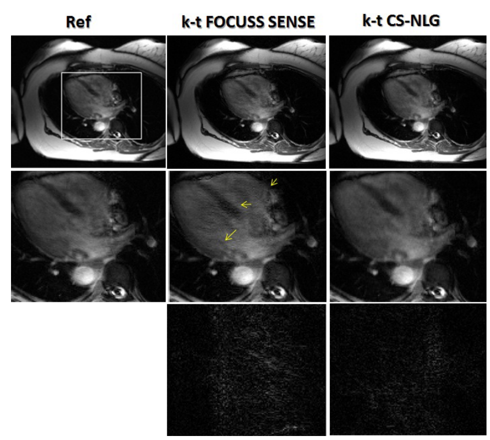

Fig.2. Full reconstructions (top), ROI (middle) and difference images (bottom).

RESULTS AND DISCUSSION:
The feasibility of the proposed method was validated on a set of cardiac cine data acquired using a 2D true FISP sequence with a flip angle of 50 degree and TE/TR=1.87/29.9 msec. The full dataset was of 256×216×20×4 (#frequency encoding × #phase encoding × #frame × #coil). The FOV in the readout direction was 34 cm, bandwidth was 930 Hz/pixel, and the slice thickness was 6mm. For the proposed method, the reduction factor is 2 for NL-GRAPPA and 5 for CS, and ACS is 32 (net reduction factor of 4.23). The reconstructions using full data, *k-t* FOCUSS with sensitivity encoding [8] and the proposed *k-t* CS-NLG were shown in Fig. 2 for comparison. The proposed method is seen to have fewer artifacts and preserve more details in the ROI than *k-t* FOCUSS. The superiority of the proposed method is also demonstrated in the difference images. We also show the temporal profile of the original, *k-t* FOCUSS with SENSE, and the proposed *k-t* CS-NLG in Fig. 3. The proposed method is able to better capture the temporal variations than *k-t* FOCUSS with SENSE.

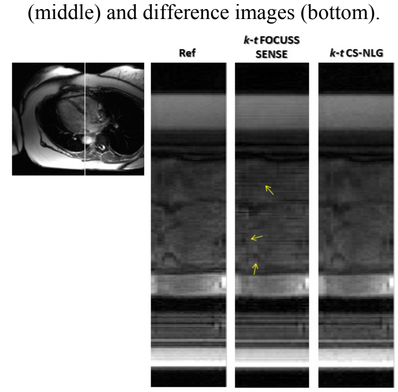

Fig.3. Comparison of the temporal profiles. From left to right: white line indicating the location, reference, *k-t* FOCUSS with SENSE, and *k-t* CS-NLG.

CONCLUSION:
We propose a novel dynamic MRI reconstruction technique that combines CS with parallel imaging. The proposed method is able to preserve both spatial resolution and temporal variations at high accelerations.

REFERENCES:
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