Parallel Reconstruction Observing Self consistency and Temporal smoothness (PROST)

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Introduction: Spatial and temporal prior information has been increasingly explored for accelerating time resolved imaging. Previously, kt-GRAPPA and other methods (1-3) exploit temporal redundancy, but are restricted to strict Cartesian sampling or calibration kernels with specific patterns. kt-SPARSE, kt-FOCUSS and kt-SPIRiT (4-6) allow for arbitrary sampling while constraining temporal sparsity in an L1 sense, which may not always be optimal if the signal is not highly compressible. Here we propose PROST (Parallel Reconstruction Observing Self consistency and Temporal smoothness) which is implemented by extending the SPIRiT self-consistency kernel to the time domain enforcing temporal smoothness in k-t space while allowing arbitrary view ordering as in the original SPIRiT formulation (7).

Theory: PROST is based on the assumption that each temporal phase has small changes with respect to its neighbors (temporal smoothness). To incorporate temporal smoothness, a spatial and temporal kernel (figure 1) is calibrated from training data that is acquired at each time point. Principal components analysis (PCA) is incorporated into PROST to further express the information redundancy in the temporal dimension thereby reducing the number of unknowns (8,9). PROST can be formulated as a least squares minimization: $\mathbf{argmin_x}||\mathbf{DBx-y}||^2 + \boldsymbol{\lambda}||(\mathbf{G-I})\mathbf{Bx}||^2$. Where **y** is the sampled data in k-space and all time and **Bx** is the reconstructed k-space data over all time. **G** is the grappa kernel, which extends over the k-space, the coil as well as the time dimension (figure 1). **D** is a projection onto the acquired k-space lines, **B** is the temporal basis derived from a principal components analysis of the fully acquired center of k-space and x are the unknown spatial weights of the k-space data in the **B** basis. The conjugate gradient algorithm was used to solve the minimization problem.

Methods: Optimization was carried out on a retrospectively under-sampled CINE scan by varying the number of training lines, number of principal components and kernel sizes. After optimization, a pulse sequence was developed to implement a truly under-sampled data acquisition with semi-random Cartesian golden ratio view ordering. 8 healthy volunteers were scanned at 1.5 T. CINE imaging was carried out at 1x under-sampling and 6x (true) under-sampling including 6 training lines for PCA and kernel calibration. Scan parameters were: 256x192 matrix. .75 PFOV, **1** NEX, 8 views per segment (VPS) and 12-14 slices (6 mm thick; 4 mm gap). Scan times varied based on heart rates. The 6x under-sampled scan required 3-4 breath-holds for whole heart coverage compared to 12-14 breath-holds (depending on the number of slices) for fully sampled reference scans. MATLAB (Mathworks, Natick MA) was used for reconstruction. Ejection fraction was determined by an experienced reader.

Results: Optimal parameters were as follows: [3x3x3] kernel size, 10 principal components and 6 training lines. These parameters were used for comparison of PROST, PROST without PCA and SPIRiT using temporal updates as in (7) on a retrospectively under-sampled dataset (figure 2). Volunteer data from a fully sampled scan as well as data from a scan under-sampled at a true reduction factor of 6 is shown in figure 3. Ejection fraction for the fully sampled dataset was 64.2 ± 4.0 % (mean ± std. dev) and the under-sampled data gave an ejection fraction of 65.2 ± 3.3 %. These values were not statistically different (p = 0.11).

Discussion: PROST is a SPIRiT based method that imposes temporal smoothness while allowing for arbitrary view orders. As shown in figure 2, PROST improves error performance compared to regular SPIRiT. During optimization, PCA improved convergence from 31 iterations (PROST w/o PCA) to 24. PCA only improved error in diastole where temporal changes are slower and easily compressible. In volunteers, reconstruction error was reduced with higher temporal resolution (8 VPS or less), due to the inherent assumptions in PROST about temporal smoothness. When used for CINE imaging, PROST gives similar ejection fraction values when compared to fully sampled data. Extensions include adding additional regularization such as L1 (4-6) and utilizing spiral/radial trajectories (3,7). PROST can be used to significantly improve temporal resolution while keeping (or reducing) the total scan time.

References: *(1) Huang et al. MRM 2005. 54, 1172-84; (2) Taso et al. MRM 2003. 50, 1031-42; (3) Seiberlich et al. MRM 2011; (4) Lustig et al. ISMRM 2006; (5) Jung et al MRM 2009; 61:103-116.; (6) Lai et al. ISMRM 2010.; (7) Lustig et al. MRM 2010. 64, 457-71;(8)Pedersen et al. MRM 2009. 62, 706-16; (9) Liang IEEE ISBI 2007. 988-91*

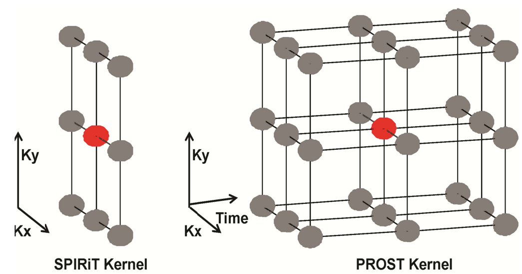

Figure 1: The standard SPIRiT kernel and the spatio-temporal SPIRiT kernel used in PROST. The red sphere is fit using neighbors (grey) in k-space (SPIRiT) and both k-space and time (PROST). For simplicity, the coil dimension is not shown.

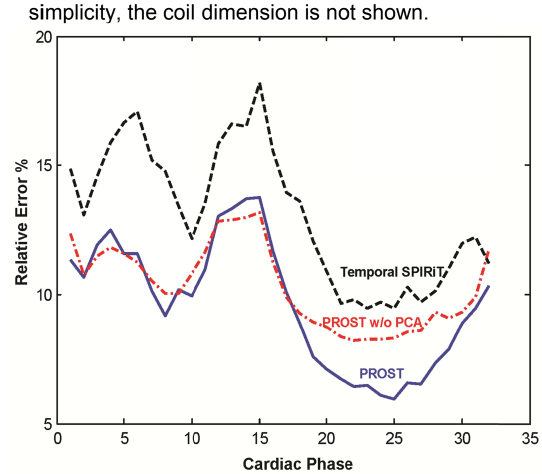

Figure 2: Comparison of PROST, PROST without PCA and SPIRiT in one healthy volunteer.

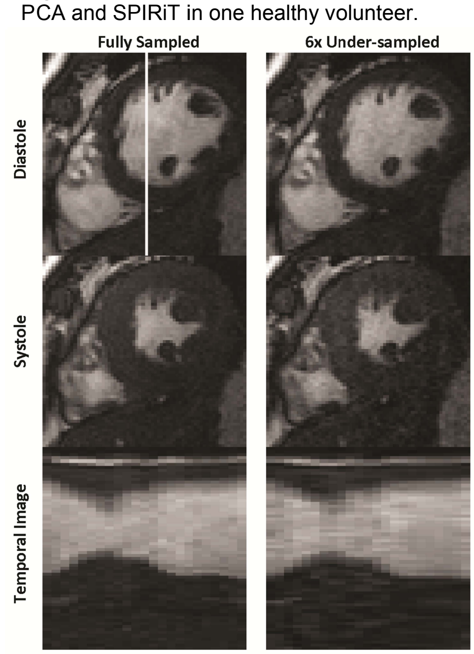

Figure 3: CINE images reconstructed with fully sampled and truly 6x under-sampled data in one volunteer. The time-course of an intensity profile (top left image) is shown.