Beyond Low Rank + Sparse: Multi-scale Low Rank Reconstruction for Dynamic Contrast Enhanced Imaging

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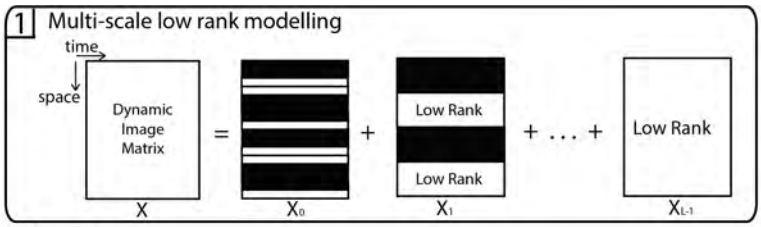

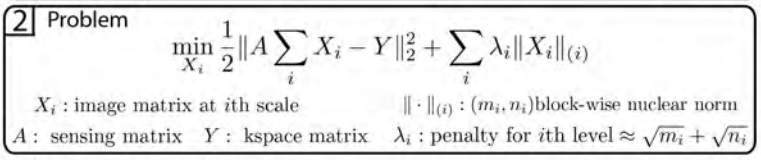

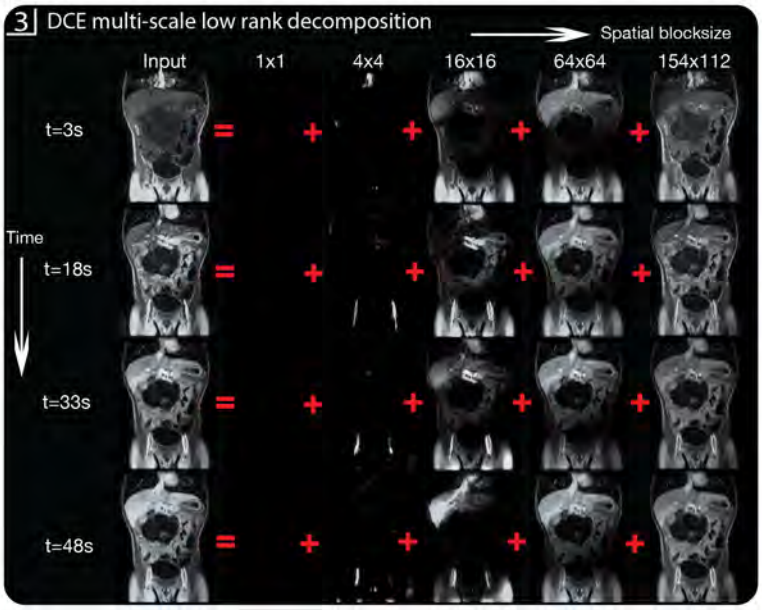

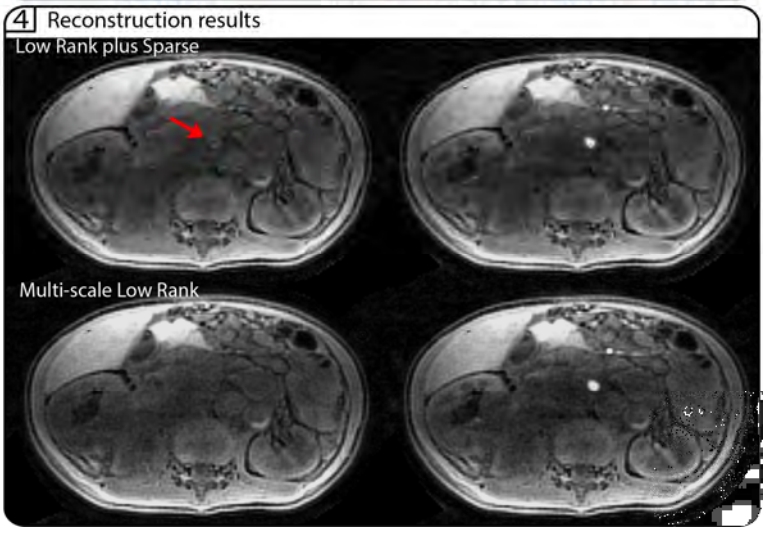

TARGET AUDIENCES: Those interested in dynamic imaging, low rank signal modeling, sparse sampling.

PURPOSE: Dynamic Contrast Enhanced (DCE) MRI is a powerful method that can provide comprehensive information to characterize lesions. High temporal resolution is often desired for 3D DCE, but at the cost of lower spatial resolution. Low rank / partial separable methods[1-4] offer an effective way of balancing this tradeoff by exploiting spatio-temporal correlations of dynamic images. However, existing low rank methods model contrast dynamics either globally, locally or globally with sparsity and do not capture spatio-temporal correlations in intermediate scales. In this work, we present a new multi-scale low rank reconstruction method that can effectively capture spatio-temporal correlations at different scales, thereby providing a more accurate reconstruction.

METHODS: We model contrast dynamics in DCE at different scales as block low-rank matrices over time with different block sizes (Fig. 1). We approach the problem via a convex demixing formulation[5] and for each block we use the nuclear norm as the convex surrogate for matrix rank (Fig. 2). Penalizing parameters are chosen proportional to the block size. Update steps can be derived using ADMM.[6]

The proposed multi-scale low rank reconstruction is combined with ESPIRiT[7], a compressed sensing and parallel imaging reconstruction algorithm and was compared with locally low rank[3] (8×8 spatial block size) and low rank plus sparse[4] modeling. To evaluate the reconstruction performance, a free breathing DCE dataset was acquired in a pediatric patient with 18 contrast phases, matrix size 192×156×100, 1×1.4×2 mm^3 resolution, and ~8 s temporal resolution. Soft gating was used according to Cheng et al[8]. The acquisition was performed on a 3T GE MR750 scanner with a 32-channel cardiac array using an RF-spoiled gradient-echo sequence. The total acceleration factor per temporal phase was ~8.

RESULTS AND DISCUSSIONS: Figure 3 shows the result of multi-scale low rank decomposition on a fully sampled dataset over time. Small contrast dynamics in vessels are captured in 4×4 blocks while bigger contrast dynamics in the liver are captured in 16×16 blocks. The biggest block size captures the static tissues and interestingly the respiratory motion. Figure 4 shows the comparison results. Low rank plus sparse reconstruction displays artifacts around the pulsatile flow, which is neither globally low rank nor sparse, but rather locally low rank. Locally low rank reconstruction captures the correct dynamics but exhibits more flickering artifacts (can be viewed at http://youtu.be/ff-MLrF2oJc). Multi-scale low rank reconstruction offers a balance between two methods.

CONCLUSIONS: The proposed multi-scale low rank reconstruction exploits spatio-temporal correlations at all scales and provides a more accurate DCE reconstruction. The code will be available online.[9]

REFERENCES: [1] Liang, et al. ISBI 2007; 988-91. [2] Zhang, et al. JMRI 2013; doi 10.1002/jmri.24551. [3] Otazo, et al. MRM 2014; doi 10.1002/mrm.25240. [4] Lingala, et al. IEEE TMI 2011; 30:1042-54. [5] McCoy, et al. arXiv:1309.7478. [6] Boyd, et al. Foundations and Trends in Machine Learning 2010; 3:1-122. [7] Uecker, et al. MRM 2014; 71: 990-1001. [8] Cheng, et al. JMRI 2014; doi 10.1002/jmri.24551. [9] BART. (2014) doi: 10.5281/zenodo.12495