Improving Compressed Sensing Parallel Imaging using Autocalibrating Parallel Imaging Initialization with Variable Density Tiled Random k-space Sampling

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Introduction: Imaging speed is demanded for many 3D MRI applications requiring high spatial resolution and large volume coverage. To further push the acceleration capability, several compressed sensing (CS) parallel imaging (PI) methods have been developed utilizing both coil sensitivity and intrinsic image sparsity [1,2,3]. While demonstrating improvement over PI or CS alone, most methods in this category necessitate iterative data processing that is highly computationally intensive to enforce PI and CS constraints in reconstruction. A recent study demonstrated that the number of iterations can be largely reduced by improving the initial solution using autocalibrating PI [4]. This work was aimed to further improve compressed sensing parallel imaging in terms of image quality by optimizing k-space sampling.

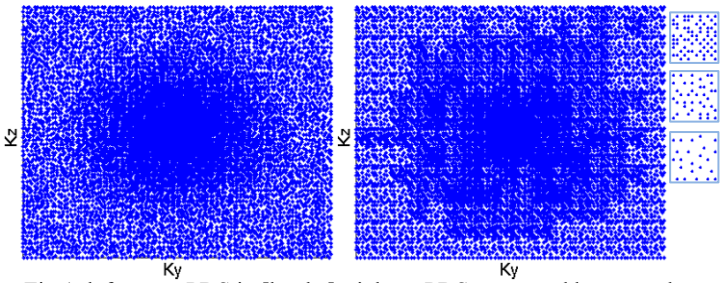

Fig.1. left: true vPDS in [ky, kz]; right: vtPDS generated by properly tiling the 3 small PDS patterns on the right

Theory: Incoherent k-space sampling needed for CS is not desirable for autocalibrating PI, because its random sampling generates a formidably large number of synthesis patterns and consequently makes PI initialization itself extremely time-consuming. To address this challenge, a tiled-Poisson disk sampling (tPDS) scheme was developed by repeating only a few small Poisson disk sampling (PDS) patterns in k-space [4]. By this means, much fewer synthesis patterns are produced enabling fast PI initialization. A general rule in MRI is that center k-space possesses most signal energy and is of higher importance for image reconstruction. From the reconstruction accuracy perspective, variable density PDS (vPDS) with denser sampling at center k-space (Fig.1.a) would be more desirable than PDS and tPDS with uniform k-space sampling density. Here, we extend the tPDS scheme to variable-density tPDS (vtPDS) as below. First, a few small PDS patterns, each of which has different sampling density (around user-prescribed acceleration), are generated and then are randomly tiled in k-space with pattern-specific k-space-radius-dependent probability. More specifically, low-acceleration patterns are selected with higher probability near center k-space and high-acceleration patterns are more frequently selected when approaching outer k-space. As shown in Fig.1.right, k-space sampling generated by this means incorporates variable density sampling in incoherent k-space sampling needed for CS. Furthermore, compared to PDS and vPDS that result in a quadratically increasing number of synthesis patterns, vtPDS generates much fewer (~2000) synthesis patterns regardless of the increase in imaging resolution (Fig.2).

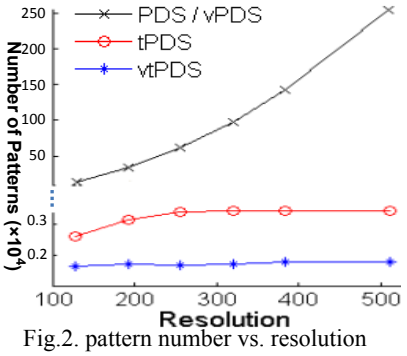

Fig.2. pattern number vs. resolution

Methods & Materials: The proposed sampling scheme was evaluated in comparison with conventional tPDS sampling. For this purpose, full k-space was acquired from 4 healthy volunteers on a GE 1.5T system using 8-channel coils (1. T2w brain MRI; 2. PDw knee MRI; 3. noncontrast-enhanced renal MRA; 4. whole-heart coronary MRA) and downsampled off line to simulate tPDS and vtPDS acquisitions with the same net acceleration (3.7~4.3×). For image reconstruction, an initial solution was generated by ARC (autocalibrating reconstruction for Cartesian sampling)[5] and then processed using ESPIRiT [6], a computationally efficient approach combining PI and CS, with 20 iterations.

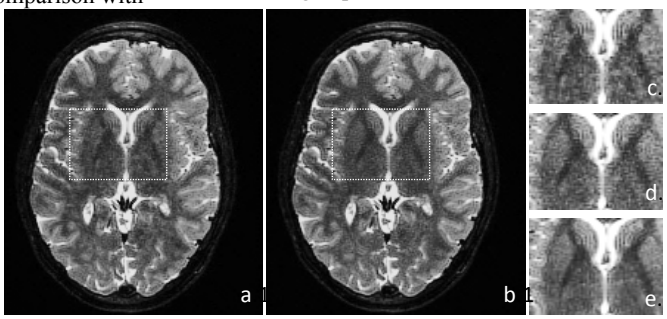

Fig.3 T2w Brain with 4.3×: a) tPDS, b) vtPDS, c & d are zoom in of the box in a & b, e) reference from full k-space

Results: On all 4 datasets, vtPDS provided more accurate reconstruction than tPDS (RMES: 13.3±3.8% vs. 14.7±4.3%). As shown in Fig. 3, vtPDS clearly outperforms tPDS on T2w brain MRI and improves the edge delineation of the grey matter border (Fig.3.c-e). Fig 4 compares renal MRA images. tPDS reconstruction (a) shows visible ghosting-like artifacts (arrows in a), presumably due to larger errors near center k-space and unsmooth sampling density transition from fully sampled calibration region to undersampled outer k-space, while both vPDS and vtPDS suppress such artifacts and remarkably improve kidney depiction. However, PI initialization for vtPDS is ~10× faster than that for vPDS.

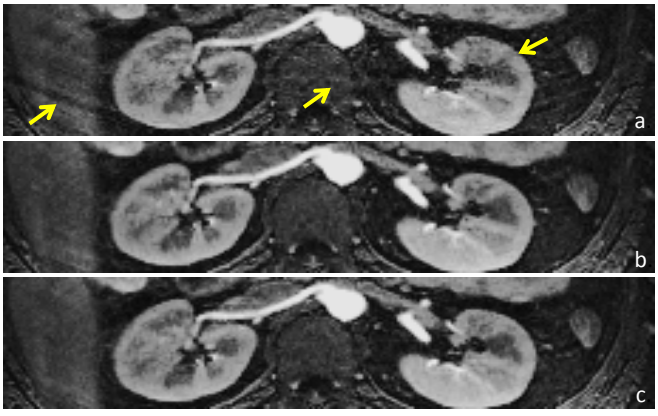

Fig.4 Renal MRA 3.7×: a) tPDS, b) vPDS, c) vtPDS

Conclusion: This work developed a new k-space sampling scheme, vtPDS, that addresses incoherent sampling needed for CS and a small number of synthesis patterns required for efficient PI initialization, and meanwhile provides a flexible scheme to perform variable density sampling that is preferred for reconstruction accuracy. Our results show that vtPDS can improve reconstruction compared to tPDS with the same net acceleration and also provides results comparable to true vPDS without increasing computation burden for PI initialization like vPDS.

References: [1] King, ISMRM, 2008:1488; [2] Liu, ISMRM, 2008:3154; [3] Lustig ISMRM, 2009:334; [4] Lai, ISMRM Parallel Imaging Workshop, 2009; [5] Beatty, ISMRM 2007:1749; [6] Lai, ISMRM, 2010:345