An efficient scheme of trajectory optimization for both Parallel Imaging and Compressed Sensing

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Target Audience: Scientists and clinicians interested in highly accelerated MRI

Purpose: Long acquisition times make images vulnerable to motion artifacts and limit clinical adoption. Undersampling of *k*-space is a widely adopted approach for fast imaging. Several reconstruction methods were proposed to recover the undersampled dataset, in which the combination of Partial Parallel Imaging (PPI) and Compressed Sensing (CS) is a promising approach to achieve low noise/artifact level [1]. Instead of using a fixed sampling trajectory, trajectory optimization has been proposed for both PPI[2] and CS[3] for significantly improved reconstruction. However, the expensive computational costs of these existing methods prevent their clinical application. Here we present a clinically applicable scheme which efficiently optimizes the sampling trajectories to achieve better performance for both Parallel Imaging and Compressed Sensing.

Methods: We proposed a highly efficient trajectory optimizing scheme, which uses reference data from one scan among a series of scans of a clinical exam. The steps of the algorithm are shown in Fig. 1. There are following four main features:

1) An iterative random optimization scheme (heuristic *Simulated Annealing*) is used;
2) A GRAPPA-operator[4] is pre-computed based on the reference data, and the *k*-space extrapolation using GRAPPA-operator is pre-calculated before iterations;
3) A fast *pseudo-reconstruction* is implemented in each iteration;
4) L_p Norm of errors in image domain is used as an objective function to balance PPI and CS.

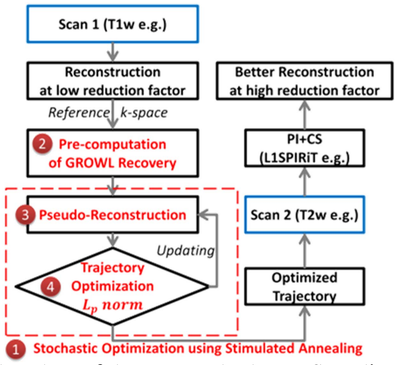

Fig. 1 Flowchart of the proposed scheme. Sampling trajectory is optimized using Stimulated Annealing. This scheme is highly efficient due to pre-computation and *Pseudo-Reconstruction*

Simulated Annealing[5] is a stochastic optimization strategy widely used to search global optimal solutions using a statistical updating criterion. ***Pre-computation***: Before iterations of optimization, a GRAPPA operator is pre-calibrated using reference *k*-space. Extrapolation using a 1-by-5 GRAPPA-operator can help to accurately expand a sampled *k*-space line and recover the two adjacent k-space lines. The extrapolation is independent of the entire sampling trajectory. ***Pseudo-Reconstruction***: Instead of implementing the nonlinear reconstruction algorithm repeatedly, any un-acquired *k*-space lines can be recovered by GRAPPA-operator if there is any sampled line close-by. Given a trajectory, a fast *pseudo-reconstruction* can be easily generated using the pre-computed GRAPPA-operator left/right extrapolation results. At locations without adjacent acquired line, zero-filling is used. The Pseudo-reconstruction results in up-to 3 times lower reduction factor without true parallel imaging calculated in iterations. **Objective Function:** We used the magnitude peaks of the errors between pseudo-reconstructed image and reference image as the objective function, which is quantified using L_pNorm (ex. p=∞). Since CS is good at suppressing noise-like artifacts, minimizing L_pNorm of recovery errors can balance performance of both PPI and CS.

Results: Here we implemented the trajectory optimization scheme using T1w and T2w brain datasets. The trajectory optimized from T1w data was applied to both T1w and T2w data to demonstrate the applicability of the optimized trajectory for scans with different contrasts. These two datasets (FFE sequence/230×230 mm^2/256×256 matrix) were acquired on a Philips 3T system (Philips Healthcare, Best, the Netherland) with an 8-channel head coil (Invivo Corporation, Gainesville, FL). The datasets were all fully sampled and retrospectively undersampled for testing. 1-D undersampling trajectory along PE direction (left-right) was optimized on T1w data using the proposed scheme with reduction factor of 5. Fig. 2 shows the change of objective function (energy in stimulated annealing) in optimization iterations and the correlation between objective function values and RMSE of reconstruction using L1-SPIRiT[1], CS-SENSE[6] and L1-SPIRiT with spatially adaptive regularization [7,8]. Fig. 3 shows the comparison of the reconstructed images of T1w and T2w datasets using L1-SPIRiT (20 iterations) with spatially adaptive regularization, with the proposed optimization and without (using a conventional point-spread-function based 1D variable density random trajectory[1] instead). Optimizing the 1D random undersampling trajectory takes **only 30 seconds** with Matlab on a laptop with 2.4GHz Duo CPU without intended acceleration for code.

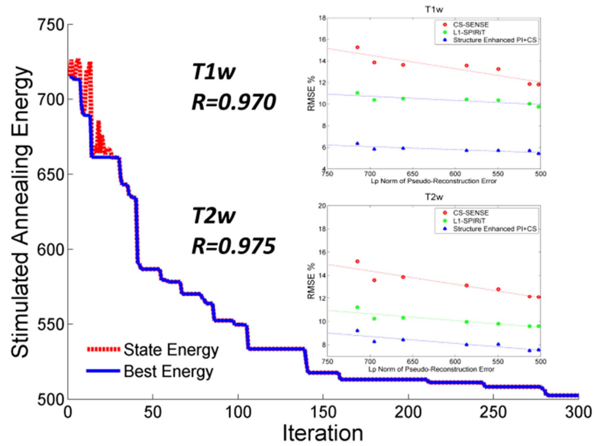

Fig. 2 The objective function changes in the optimization iterations. The L_p Norm chosen is correlated with RMSEs of recovery using several reconstruction methods with PPI & CS.

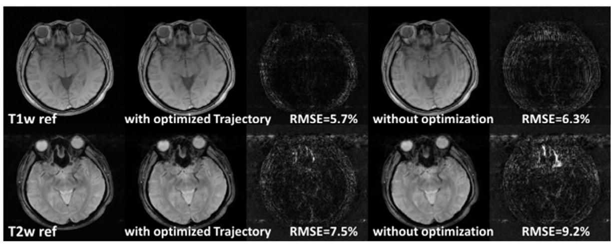

Fig. 3 Comparison of the reconstructed images at reduction factor of 5 with and without trajectory optimization based on T1w data. Optimized trajectory results in better reconstruction performance with lower RMSE for both T1w and T2w scan.

Discussion: Parallel imaging reconstruction is only processed one time in the pre-computation before main optimization iterations in the proposed scheme. Fast *Pseudo-reconstruction* without any repeated expensive approaches is implemented based on the fact that the GRAPPA operator is not affected by the trajectory. Hence, the proposed method is fast. The L_p Norm, instead of conventional RMSE, is chosen as the objective function because CS recovery's performance is limited for large intensity error in the initialization. Thus, we chose to minimize the error peaks with L_p Norm, which reduces the initial artifacts for CS. Moreover, Fig. 2 validates the method and shows the objective function is correlated with the RMSE of several reconstruction methods using PPI and CS. Fig. 3 shows it is applicable to use the first scanned image set to optimize the trajectory and the same trajectory can also be applied for following scans with the same Field of View.

Conclusion: Here we presented an efficient scheme for clinically applicable trajectory optimization using one scan in the exam as reference. Experiments on in-vivo datasets illustrated the proposed scheme results in great improvement of reconstruction and good applicability for optimize multi-scan acquisition.

References: [1] Lustig M, et al. MRM 2010; 64(2):457-471[2] Xu D, et al. ISMRM 2005; p2450 [3] Seeger M, et al. MRM 2010; 63:116-126 [4] Lin W, et al. MRM 2010; 64(3):757-7665 [5] Kirkpatrick S, et al. 1993; [6] Liang D, et al. MRM 2009;62:1574–1584 [7] Gong E, et al. ISMRM 2012; p2269 [8] Huang F, et al. ISMRM 2012; p2539