A Clinically Applicable Scheme of MRI Trajectory Optimization for 3D Cartesian Acquisition

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Target Audience: MR researchers and clinical scientists working on fast acquisition.

Purpose: Random undersampling is an important component used with Parallel Imaging[1, 2] (PI), Compressed Sensing[3] (CS) and their combination (PI-CS)[4] for fast acquisition. Optimized pseudo-random trajectory results in better reconstruction yet the computation complexity of optimizing undersampling trajectory prevented it from clinical application. Lately, we proposed an efficient scheme[5, 6] for 1D random undersampling optimization using stochastic method and reference *k*-space data. Here we extended and improved the scheme to optimize the 2D Cartesian undersampling in 3D acquisition for PI and CS, by using Nonlinear Grappa Operator[7] and Coherence[8] based objective function. In-vivo experiments showed improved reconstruction using PI-CS.

Methods: The basic optimization scheme is similar to 1D undersampling optimization scheme[5,6] which optimizes the subset of *k*-space to be sampled using reference *k*-space from previous scans of similar positions and/or with different contrasts. The flowchart is shown at Figure 1. The main concept of the efficient scheme is: to replace computational-costly reconstruction steps in stochastic optimization iterations with efficient Pseudo-reconstruction[5,6] which only uses linear combination of pre-computed Parallel Imaging Operator results, and to use an objective function to approximate RMSE based on the Pseudo-reconstruction error. **To better optimize 2D trajectories, we chose to use a nonlinear GRAPPA operator[7] (fig. 2) and a Coherence based objective function to better approximate the RMSE of PI-CS.**

1. **A modified Simulated Annealing** was implemented with a Gene-Algorithm based heuristic to optimize 2D sampling trajectories[6].
2. **A 3x3 Nonlinear GRAPPA Extrapolation operator**[7] was calibrated using the reference *k*-space to accurately extrapolate the neighbour samples. Since the kernel size is very small, nonlinear operator which maps the data to a higher dimension of virtual coils performs better than conventional GRAPPA. The extrapolation result was only computed once since they are not related to undersampling trajectories.
3. **Pseudo-Reconstruction:** For any arbitrary trajectory, un-acquired samples in *k*-space can be recovered using the pre-computed Nonlinear GRAPPA-operator results from sampled neighbour *k*-space data, which only needs efficient linear combination.
4. **Coherence based Objective Function** was used to compare two trajectories and update current optimal solution in iteration of stochastic optimization. Instead of error peak, we defined a new objective function to achieve more accurate prediction of the recovery performance using both PI and CS. In CS, incoherence of the sampling matrix $\boldsymbol{D}$, which equals to the peak non-dc value in point spread function[3], is the key for the convergence of l_1 regularized optimization[3]. Here we used the modified PI-recovery based point spread function (PSF) $\boldsymbol{psf(D) = \mathcal{F}^{-1}\hat{D} = \mathcal{F}^{-1}(D + E(D))}$, in which $\mathcal{F}$ for Fourier transform. $\hat{\boldsymbol{D}}$ is the pseudo-sampling operation resulted from pseudo-reconstruction results, which is a combination of $\boldsymbol{D}$, sampling operation (1 for sampled points), and $\boldsymbol{E}$, the normalized accuracy of pseudo-reconstruction ($E \approx 1$ if perfectly recovered). The objective function was modified accordingly: $\boldsymbol{f(D) = \|psf(D)\|_p, p \gg 1}$.

Results: Two brain T1w/T2w datasets (FFE sequence/ 230×230mm^2/256×256 matrix/16 slices) 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 under-sampled. 2D random sampling trajectories were optimized and compared with VD Poisson Disk random trajectory[4]. The optimization scheme took about 30 seconds on Matlab on a 2.4GHz Quad CPU 64bit system. The T1w dataset was used for trajectory training, and the optimized trajectory was applied for reconstruction of another image. Figure 3 compared the L_1-SPIRiT reconstruction using optimized and un-optimized trajectories. Figure 3e showed the decreasing of objective function in iterations in the stochastic optimization. Figure 4 showed the approximation of RMSE of different trajectories regressed from the objective function with/without using Nonlinear GRAPPA.

Discussion: The proposed method efficiently optimized the 2D Cartesian trajectories in 3D acquisition. To tackle the problem with high degree-of-freedom, nonlinear GRAPPA operator was used to accurately extrapolate data in *k*-space and pre-computation enabled fast pseudo-reconstruction given any trajectory in stochastic optimization. The modified Coherence based objective function better approximates the performance of CS after PI-based recovery to better predict RMSE of PI-CS reconstruction. Results showed the scheme was efficient and effective for 2D Cartesian trajectory optimization. This scheme can benefit fast 3D acquisition and Multi-contrast imaging [5]. This scheme is also adaptable for non-Cartesian sampling by gridding the Nonlinear GRAPPA of non-Cartesian samples to Cartesian points in pre-computation step.

Conclusion: We presented an efficient scheme for 2D Cartesian trajectory optimization in 3D acquisition which can be applied clinically.

References: [1] Pruessmann et.al MRM 1999 [2] Griswold, et.al. MRM 2002 [3] Lustig et. al. MRM 2007 [4] Lustig et. al. MRM 2010 [5] Gong et.al. ISMRM 2013 [6] Gong et.al. Sedona 2013 [7] Chang, et.al. MRM 2012 [8] Donoho, et.al. IEEE TIT 2006

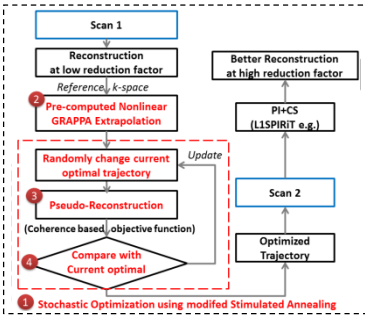

Figure 1 Flowchart of the trajectory optimization scheme.

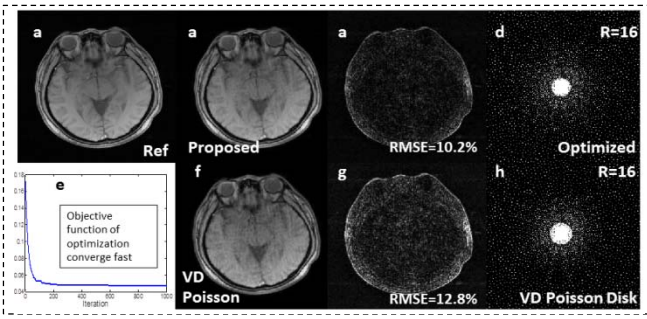

Figure 3 Reconstruction using L_1-SPIRiT at R=16 with non-optimized and optimized trajectories. (a) Ref (b)-(d) with optimized trajectory, (f)-(h) with VD-Poisson-Disk trajectory (e) fast convergence of objective function in optimization.

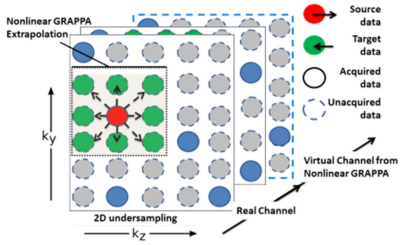

Figure 2 Diagram of the used nonlinear GRAPPA extrapolation operator. The operator extrapolates missing data while projecting it to virtual channels.

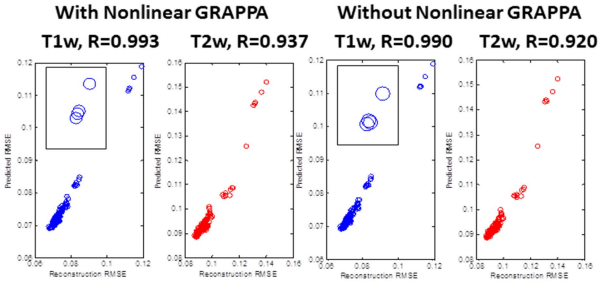

Figure 4 Comparison of the regressed RMSE from objective function with/without using Nonlinear GRAPPA. Zoom-in view of selected regressed results showed better distinguish using Nonlinear GRAPPA.