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

Purpose: Random undersampling is an important component used with Parallel Imaging (PI), Compressed Sensing (CS) and their combination (PI-CS) 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 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 and Coherence based objective function. In-vivo experiments showed improved reconstruction using PI-CS.

Methods: The basic optimization scheme is similar to 1D undersampling optimization scheme 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, 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 (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.

2. A 3x3 Nonlinear GRAPPA Extrapolation operator 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 $D$, which equals to the peak non-zero value in point spread function, is the key for the convergence of $l_1$ regularized optimization. Here we used the modified PI-recovery based point spread function (PSF) $f(D) = F^{-1}D = F^{-1}(D - E(D))$, in which $F$ is the pseudo-sampling operation resulted from pseudo-reconstruction results, which is a combination of $D$, sampling operation (1 for sampled points), and $E$, the normalized accuracy of pseudo-reconstruction ($E \approx 1$ if perfectly recovered). The objective function was modified accordingly: $f(D) = \| psf(D) \|_p \gg 1$.

Results: Two brain T1w/T2w datasets (FFE sequence/ 230x230mm$^2$/256x256 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. 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 L1-SPIRiT reconstruction using optimized and un-optimized trajectories. Figure 3e showed the decreasing of objective function in iterations of 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. 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.


Figure 1 Flowchart of the trajectory optimization scheme.

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

Figure 3 Reconstruction using L1-SPIRiT at R=16 with non-optimized and optimized trajectories. (a) Ref (b)-(d) with optimized trajectory. (e)-(h) with VD-Poisson-Disk trajectory (e) fast convergence of objective function in optimization.

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.