

# Accurate iterative reconstruction algorithm from Undersampled Radial trajectory

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**Introduction:** Radial k-space sampled data can be reconstructed using a variety of schemes such as gridding, filtered back-projection (FBP), etc. Of these, the gridding algorithm [1] has been widely used due to its simplicity and speed. Alternative approaches can be more reliable when improved accuracy is desired and/or when finding the accurate density compensation function becomes non-trivial. Recently, the iterative next-neighbor regridding (INNG) algorithm was proposed as a means for accurate reconstruction since the algorithm is based on semi-sinc interpolation [2]. The INNG algorithm is one of the projections onto convex sets (POCS) type algorithms and can be used to reconstruct images from undersampled k-space data. However, when used for the undersampled radial trajectories, compared to gridding and FBP, INNG shows blurred profiles due to its lack of high frequency information [3].

In this abstract, work on combining INNG algorithm with a phase constrained process is presented to improve the reconstruction performance.

**Methods:** Fig. 1(a) shows the process of the INNG algorithm. The original INNG algorithm consists of the following six steps: Suppose that the original designed Cartesian grid size of the image is  $N \times N$ . 1) Distribute the k-space data to a larger rescaled matrix. Typically, the rescaling factor is defined as  $s$ , where  $s = 2^n$  and  $n$  is a small positive integer. The location of each datum in the large rescaled matrix is determined by multiplying the original k-space coordinate by  $s$  and rounding off to determine the target Cartesian grid location. 2) Perform 2D inverse FT to the rescaled matrix, converting the k-space data to image domain. 3) All rescaled matrix elements excluding the central  $N \times N$  region are replaced by zeros. 4) Perform 2D FT to the rescaled matrix, converting the image domain data to k-space.

5) After 2D FT, the original k-space data are retained at the original locations within the rescaled matrix and the other matrix elements estimated by the FT are inserted. 6) Repeat step 2) ~ 5), until a certain stopping condition is reached.

The process of the proposed algorithm is the same except for the addition of two additional processes. First, we obtain magnitude image ( $|I_0|$ ) between 3) and 4). Second, we find the phase information ( $\Phi_0$ ) from the k-space data updated from the previous iteration, and combine the magnitude image and phase information ( $|I_0| \exp(i\Phi_0)$ ) between steps 3) and 4).

To verify the reconstruction performance of the proposed algorithm, we compared it with the conventional gridding and original INNG algorithm. Conventional gridding was performed with a Kaiser-Bessel kernel, its kernel width was 4 and Voronoi density compensation was used. The original INNG algorithm and proposed algorithm used  $s = 4$ , and both algorithms used a stopping criteria = 0.001 (Eq. (8) from Ref. [2]).

We evaluated the proposed algorithm by simulating the point spread function (PSF) profiles for radial sampling trajectory. For the trajectory, 128 arms were used with each arm having 1024 data points (oversampling factor 2). The reconstructed matrix size was  $512 \times 512$ . White Gaussian noise was added to the ideal data to simulate noisy data. The mean value of the added noise was zero while the standard deviation (SD) of the noise was 20% of the average magnitude from the original ideal k-space data.

In vivo data were collected using a 3T Siemens Tim Trio MRI scanners (TR = 400ms, TE = 8.6ms, Flip angle =  $25^\circ$ , FOV =  $256 \times 256$  mm, number of arms = 128, matrix size =  $512 \times 512$ , Voxel size =  $0.5 \times 0.5 \times 2.0$  mm<sup>3</sup>). All simulations and data reconstruction were performed using MATLAB R2007b.

**Results:** Fig. 2 shows the PSF profile of the conventional gridding, INNG, and proposed algorithm. The conventional gridding profile shows more background noise while a better PSF is obtained with INNG. The proposed algorithm resulted in smaller background noise and narrower impulse. In Fig. 3, reconstructed in vivo neck images are shown using each algorithm. The reconstructed image by gridding shows visible noise while the INNG image (Fig. 3(b)) is well reconstructed, although partly blurred due to its lack of high frequency information. Our proposed algorithm's image (Fig. 3(c)) shows better performance than the other algorithms by removing the noise and blurring. The tradeoff comes in the form of prolonged reconstruction time.

**Conclusion:** We applied a phase constrained process to the INNG algorithm to improve the reconstruction performance for the undersampled radial trajectory. While maintaining INNG's accurate reconstruction performance of high SNR, high frequency information was preserved by applying a phase constraint. The algorithm can be further exploited when used with parallel imaging.

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**References:** [1] J. Ji, et al., IEEE Trans Med Imaging, 10(3), 473-478, 1991. [2] H. Moriguchi, et al., MRM, 51, 343-352, 2004. [3] W T. Wang, et al., p.2303, ISMRM, 2005.

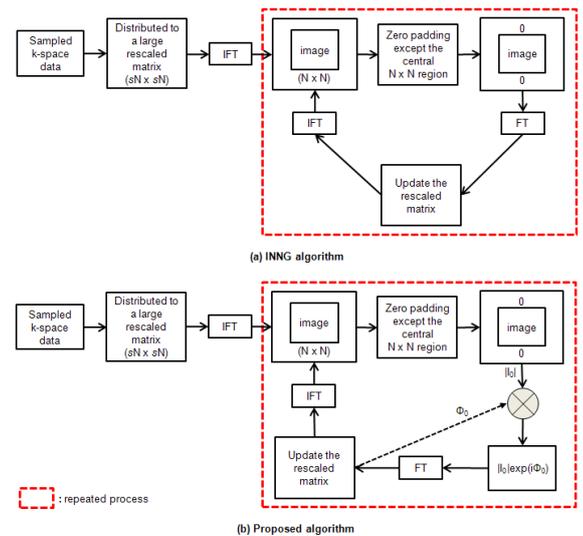


Figure 1: Flow charts of the (a) original INNG and (b) our proposed algorithm

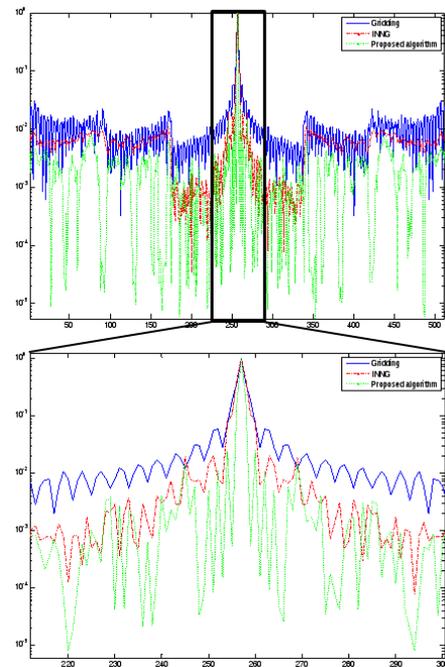


Figure 2: PSF profile (SD = 20%) of conventional gridding, INNG, and proposed algorithm. A logarithmic scale is used in the vertical axis.

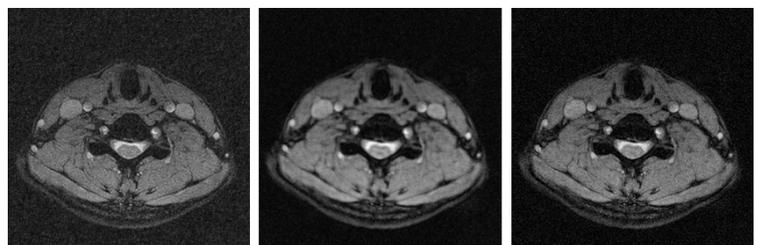


Figure 3: Reconstructed in vivo neck images by (a) conventional gridding, (b) INNG, and (c) proposed algorithm