LS_Nufft Based SENSE Reconstruction for Polar k-Space Trajectory

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Introduction

The Sensitivity encoding with arbitrary *k*-space trajectories [1] has shown its potentials of speeding up the acquisition due to a) reduced *k*-space sampling density and b) efficiency of *k*-space filling schemes. The methods of conjugate gradient (CG) as well as gridding such as NU-FFT [2], i.e. GFFT [3], and widely used Kaiser-Bessel gridding have been combined with the non-Cartesian *k*-space sampling SENSE for successful image reconstruction. Since the above gridding methods use ready-made convolution kernels, they are referred as "conventional gridding methods" [4] with trajectory–dependent image distortions. Recently, a new gridding approach named LS_Nufft [4] has been presented. LS_Nufft minimizes the reconstruction approximation error in the *Least Square* sense by generating the *k*-space trajectory-adaptive convolution kernels. Although LS_Nufft was presented for image reconstruction, it could also be introduced to the iterative SENSE reconstruction.

Methods

Sha, L. et al[4], presented the expression of 2D LS_Nufft, which calculates the *k*-space spectrum from non-Cartesian grid onto Cartesian grid. We call this expression backward LS_Nufft. For CG-SENSE reconstruction, we derived the forward expression of LS_Nufft, which calculates the *k*-space spectrum from Cartesian grid onto non-Cartesian grid:

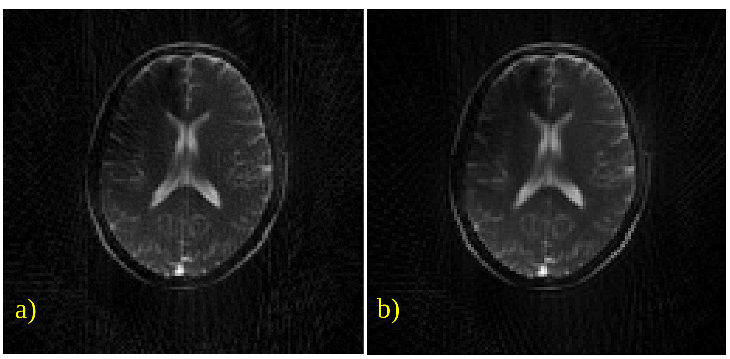
$$I^F\left(k_{xp}, k_{yp}\right) = \sum_{k1}\sum_{k2} \rho_1^* \rho_2^* I_{sc}^F\left(k1, k2\right), j1, j2 = -\frac{q}{2}, \ldots, \frac{q}{2},$$

$$I_{sc}^F = FFT\left(s_c^*(x)^{-1} s_c^*(y)^{-1} \cdot I\right),$$

where, $\left(k_{xp}, k_{yp}\right)$ is the arbitrary *k*-space point. S_c is the scaling factor. $\rho_1\left(j1, k_{xp}\right)$ and $\rho_2\left(j1, k_{xp}\right)$ are the convolution kernel matrixes. $I^F\left(k_{xp}, k_{yp}\right)$ is the non-Cartesian Fourier spectrum of image I, and I_{sc}^F is the FFT of pre-weighted image I. The iterative reconstruction algorithm using general CG method is implemented from Pruessman's original paper [1], where the gridding kernel is replaced by forward and backward LS_Nufft.

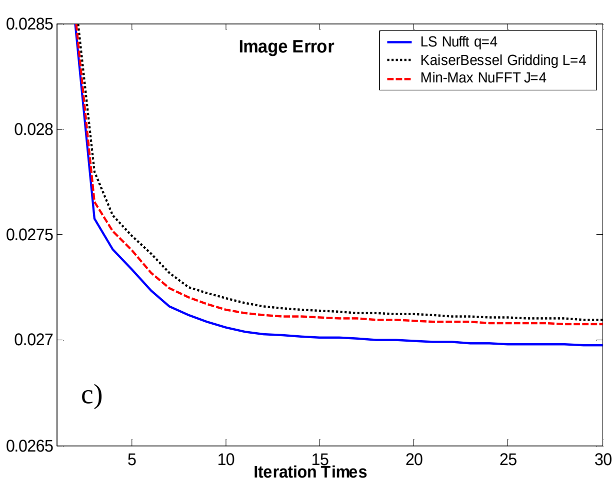
Results

The performance of LS_Nufft based iterative SENSE reconstruction was evaluated both in phantom and *in vivo* with polar sampling scheme. Simulations suggested that a considerable reconstruction result can be achieved even at a reduction factor (R) of 12, with an 8-channel receiver array. The *in vivo* raw data is acquired on a 1.5 T Siemens Symphony system with an 8-channel head coil array using True FISP protocol. 256 projections and 512 sampling points (double sampled) were acquired for a 256×256 image. 52 projections and 256 sampling points were subtracted from the original raw data to generate an under-sampled one with R=3.9 for a 128×128 image. The sensitivity maps were generated from the ripped raw data of 52 projections in a "sum-of-squares" sense [5]. The initial input image for reconstruction is shown in Figure a) and Figure b) shows the output image after 3 iterations. Image reconstruction quality can be estimated by the approximation error function defined as:



$$error(I) = \sqrt{\min_\alpha \sum_j \left|I_d(j) - \alpha I(j)\right|^2} \Big/ \max\left(\left|I_d\right|\right).$$

Where, I_d is the image reconstructed from fully encoded raw data by direct FT. The errors for all the three gridding methods, e.g., Kaiser-Bessel Gridding, Nufft using Min-Max interpolation [6] and LS_Nufft were evaluated. The results suggested a smaller deviation in the LS_Nufft method compared with the other two, which is shown in Figure c). On an Athlon XP 2500+ PC, the LS_Nufft based CG reconstruction took about 1.7 seconds per iteration while its counterpart using Kaiser-Bessel method took about 6.9 seconds per iteration. After 10 iterations, the processing can be stopped since no more improvement of the image quality is observed.



Discussion

In vivo examples showed that the proposed implementation reduced both image artifacts and reconstruction time compared with Kaiser-Bessel gridding. A real-time online reconstruction method would be accessible with the improvement in computing power.

Acknowledgements

The authors thank Guo Hua for the Matlab code of inverse LS_Nufft and thank Dr. Kannengieβer for the significative advices.

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