

Sparse k-Space Sampling Strategies and Projection-Onto-Convex Sets Image Reconstruction for Improved Fast 3D Imaging

H. Peng^{1,2}, M. Sabati^{1,2}, M. L. Lauzon^{1,2}, R. Frayne^{1,2}

¹Radiology and Clinical Neurosciences, University of Calgary, Calgary, Alberta, Canada, ²Seaman Family MR Research Centre, Foothills Medical Centre, Calgary Health Region, Calgary, Alberta, Canada

Introduction

Recent developments in three-dimensional (3D) fast MR applications [1] have focused on rapidly acquiring k -space data to reduce the scan time. One of these approaches is to completely sample the central region of the phase-encoding plane while sparsely sampling its peripheral region, resulting in the formation of sparsely sampled k -space [2]. We have demonstrated [3] that the projection-onto-convex sets (POCS) algorithm improves image quality obtained from 3D sparsely sampled k -space data, compared to the more common zero-filling algorithm [4]. It has been suggested that the quality of the reconstructed imaging (by POCS) is influenced by the specific sparse sampling strategy. In this study, we investigate whether optimal data sampling strategies exist and how they vary with relative scan time.

Methods

A moving-table CE-MRA technique [2] was used to acquire a complete raw data set of a quality-control phantom on a clinical 3 T scanner (Signa; General Electric Healthcare, Waukesha, WI). Hybrid k -space data (x - k_y - k_z with $N_x = 256$, $N_{ky} = 256$ and $N_{kz} = 64$) were produced by taking the inverse Fourier Transform (iFT) of each readout (x -direction) immediately after acquisition and then placing them into the appropriate location in the hybrid space. A series of simulated sparsely sampled k -spaces were generated (MATLAB, version 6.5.0, R13; Mathworks, Natick, MA), each with a different fully sampled central region size (α) and sparse-sampling density (β) in the peripheral region, where α was defined as the ratio between the number of data points in the central region to the points in the full phase-encoding plane, and β was defined as ratio of acquired data points to the total number of points in the peripheral region. The relative scan time τ is defined as $\tau = \alpha + (1-\alpha)\beta$. Images were reconstructed from the fully sampled hybrid k -space (*i.e.*, the true image I_0) and from simulated sparsely sampled k -spaces using POCS (I_{POCS}). Our implementation of POCS [3] forced the missing data to match the acquired data and the phase of the image to match that derived from the fully sampled central zone of k -space. The quality of the resulting images was assessed by visual inspection and quantified by the calculation of local performance errors (PE), defined as $PE = \sqrt{\sum(\zeta_i - o_i)^2} / \sqrt{\sum o_i^2}$, where ζ_i and o_i denote pixels from I_{POCS} and I_0 , respectively. The PE summation was performed over all 3×3 kernel within a local region of interest (defined in Fig 1a).

Results

In fast 3D imaging, *e.g.*, $\tau = 0.1$ to 0.2 , in order to capture dynamic information such as contrast bolus passage, it was possible to find an optimal acquisition ($\alpha_{optimal}$, $\beta_{optimal}$). The POCS images reconstructed from these optimally sampled k -space data exhibited the best visualization of high-resolution structures (Fig 1) and had decreased local PE in regions containing high-resolution structures (Fig 2). For example, when $\tau = 0.2$ (Fig 1), $\alpha_{optimal}$ and $\beta_{optimal}$ were 4.8% and 16.0% , respectively. If we collected a sparsely sampled k -space using $\alpha_{optimal}$ and $\beta_{optimal}$, the corresponding POCS reconstructed image (Fig 1c) demonstrated better resolution compared to the other sampling strategies. The local performance error value also reached its minimum under this circumstance (Fig 2). However, less dramatic changes in Local PE are seen for the longer relative scan time, *e.g.*, $\tau \geq 0.5$.

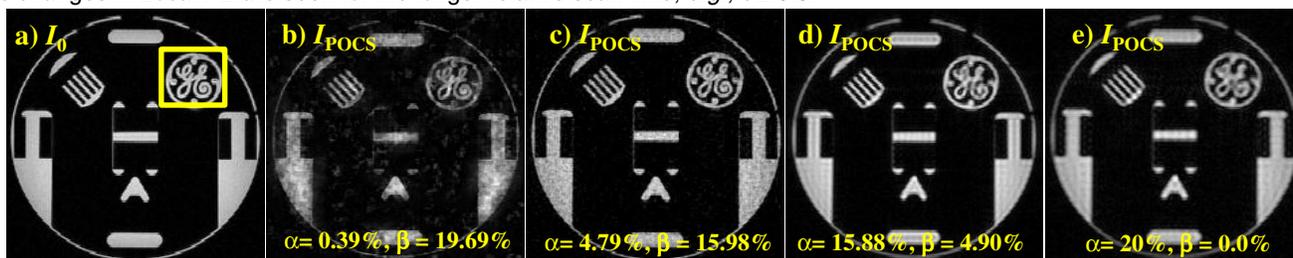


Figure 1: a) Image reconstruction I_0 from fully sampled k -space; b), c), d), e) POCS image reconstruction from a number of α , β pairs when $\tau = 0.2$. In this case, $\alpha_{optimal}$ and $\beta_{optimal}$ values reached 4.8% and 16.0% , respectively.

Conclusions

For a given relative scan time, it is possible to choose a specific sparse sampling strategy (characterized by α and β values), from which POCS image reconstruction will generate the best image to depict high-resolution structures, like small blood vessels. The choice of $\alpha_{optimal}$ and $\beta_{optimal}$ could be assessed by direct image visualization and local performance error. It was also demonstrated that when using POCS, it is advantageous to acquire some high-frequency data as opposed to spending time collecting only the central region (Fig 1c vs Fig 1e).

References

[1] Paschal, *et al. JMRI* 2004; **19**: 145–159. [2] Sabati, *et al. PMB* 2003; **48**: 2739-2752. [3] Peng, *et al. Proc ISMRM* 2005; 2301. [4] Bernstein, *et al. JMRI* 2001; **14**: 270-280.

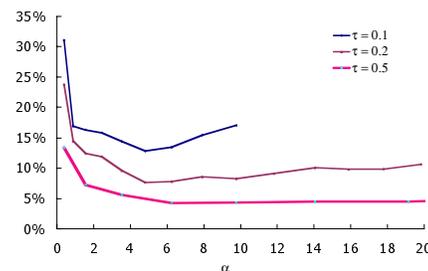


Figure 2: Local performance error (LPE) versus α for a number of relative times τ . Local PE is defined in the outlined region shown in Fig 1a. β can be calculated from $\beta = (\tau - \alpha)/(1 - \alpha)$.