Evaluation of GLACIER sampling for 3D DCE-MRI

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Target audience: Radiologists and MRI physicists who use dynamic contrast-enhanced (DCE) MRI.

Purpose: Dynamic MRI can be greatly improved through the use of sparse sampling and constrained reconstruction. Effective sparse sampling techniques must provide high spatio-temporal resolution, incoherent aliasing, and compatibility with parallel imaging. Various techniques have been proposed [1-6]. For instance, Lebel et al. used a variant of Poisson disc (PD) sampling in k_y-k_z-t space [4], and Feng et al. used a golden angle (GA) radial sampling [5], which enables flexible retrospective selection of temporal resolution. Zhu et al. used a variant of Cartesian GA called GoLden Angle CartesIan Encoded Randomization (GLACIER) [6] that randomly sub-samples each spoke (with a probability P). In this work we evaluate the performance of GLACIER sampling in DCE MRI and identify sampling probability values that provide lowest reconstruction error.

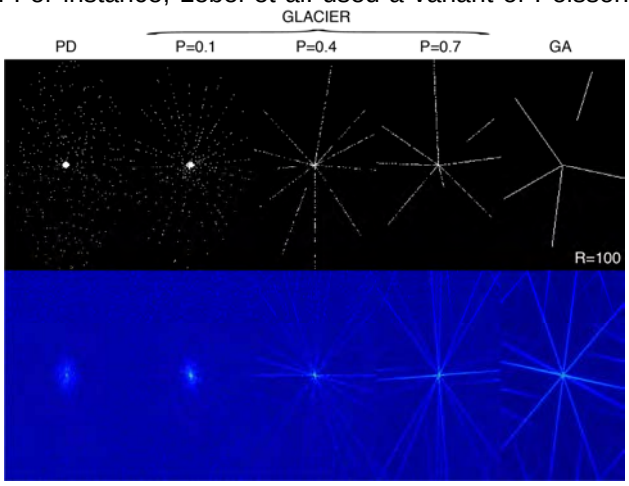

Figure 1. Sampling pattern (top) and point spread function of PD, GLACIER and GA when R=100.

Method: Fully-sampled DCE data from five brain tumor patients were acquired on a clinical 3T scanner (HDxt, GE Healthcare, Waukesha, WI) using an 8-channel head coil and T1-weighted SPGR sequence with 15° flip angle and 5.5 ms TR. Parallel imaging was turned off. The data had 256×150×10 matrix size and 22×22×6 cm^3 FOV with 35 time frames.

A single slice from each data set was retrospectively undersampled using PD, golden angle (GA) and GLACIER schemes at 20 different reduction factors (R) between 5× and 100×. We generated 50 sampling patterns for each scheme by altering the pseudorandom generator seed (PD, GLACIER) and initial angles (GA, GLACIER). We reconstructed images using the most powerful constraint, temporal total variation, with manually chosen regularization parameter. Tumor and vessel ROIs were analyzed using normalized root-mean-squared-error (nRMSE) to determine the best settings for brain DCE MRI.

Results: Fig.1 shows the sampling pattern for a single time frames for PD, GLACIER and GA when R=100 (top row). The central regions account for approximately 15% of phase encodes. The bottom row shows the corresponding point spread function (PSF). As P decreases, undersampling is more incoherent with fewer large gaps in coverage, and the PSF streaking side lobes diminish. Fig. 2 shows the mean nRMSE with the contours outlining equivalent nRMSE. The results were averaged from 5 reconstructed datasets. The advantage of GLACIER becomes evident in larger R, and is most prominent in vessels when P=0.2, and in tumors when P=0.5 (see arrows).

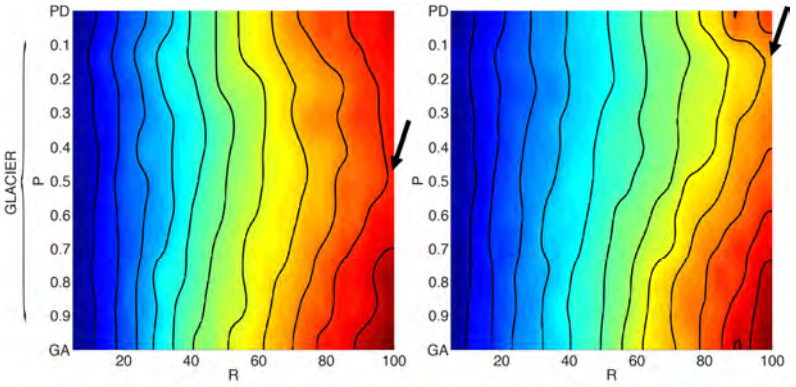

Figure 2. Mean nRMSE of (left) tumor ROI, and (right) vessel ROI.

Conclusion: We have performed retrospective evaluation of GLACIER using fully sampled in-vivo data, where the ground truth can be defined for image quality assessment. GLACIER provides the advantages of both PD and GA, and outperformed both methods at high acceleration factors. This suggests that GLACIER is an advantageous sampling strategy for 3D whole-brain DCE-MRI.

References: [1] Haider, *et al.*, MRM:60(3):749-760, 2008; [2] Lim, *et al.*, AJNR:29(10):1847-1854, 2008; [3] Saranathan, *et al.*, JMRI:35(6):1484-1492, 2012; [4] Lebel, *et al.*, MRM:71(2):635-644, 2014; [5] Feng, *et al.*, MRM:72(3):707-717, 2014; [6] Zhu, *et al.*, ISMRM, 2014, p4365.