

A Phase Constrained Graph Cut Algorithm For Reconstruction of MR Parallel Imaging Under 3D Spatial Priors

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INTRODUCTION

Current parallel imaging methods like SENSE and GRAPPA are seriously limited by SNR and g-factors associated with coil geometry. Tikhonov regularization techniques [1] using global smoothness priors can improve quality, but produce blurred images and frequently leave aliasing artifacts. In fact, most MR images have sharp edges and are piecewise smooth. A new edge preserving Markov Random Field (MRF) prior model was proposed in [2,3] to address this issue, and a new graph cut-based algorithm was developed to solve the computationally challenging non-convex optimization problem. Here we propose two important extensions of the method of [2,3] by (a) incorporating 3-D spatial priors and by jointly reconstructing multi-slice images, and (b) using low-frequency phase as a constraint during the reconstruction process. Recent reports indicate that phase-constrained reconstruction improves image quality [4]. The proposed method performs better than the conventional SENSE method applied slice-by-slice. The technique is applied to volumetric 3D MPRAGE imaging by reconstructing chunks of multiple slices at once, which also drastically reduced the computational load compared to a full 3D volumetric extension of EPIGRAM. The multi-slice approach also enabled a new calibration view sharing scheme, whereby the calibration lines were shared between adjacent slices in order to reduce acquisition time. Reconstruction results at 4-fold reduction are demonstrated for brain MPRAGE data sets, and show significant performance improvement compared to conventional SENSE at the same effective reduction factor.

METHOD

The Bayesian parallel imaging problem [2,3] reduces to the minimization of an energy function

$$E(x) = \|y - Hx\|^2 + \sum_{(p,q) \in N} V(x_p, x_q)$$

Here V is a truncated linear penalty function that encodes edge preserving piecewise smooth priors, x is the target image, y are coil outputs and matrix H captures the sensitivities of different coils. We use the graph mincut expansion move algorithm [2] to minimize $E(x)$ by successively finding the minimum energy solution of a binary optimization problem over the set of labels $L = [1, 2, \dots, N_{\text{labels}}]$. Brain MPRAGE data was acquired on a healthy volunteer with resolution (256 x 256 x 176). The k-space undersampling was performed manually by throwing away 3 out of 4 lines. The underlying graph was designed to impose spatial coherence on 3-D voxel neighborhoods (fig 1). Three adjacent slices are shown. This is in contrast to the neighborhood in [2,3] which corresponded to only the central slice.

Calibration View sharing: Calibration views were acquired at 3 times undersampling, and 3 adjacent slices were used for calibration view sharing of each slice (fig 2). 30 calibration views per slice were used, amounting to 90 calibration views for each slice after view sharing. The large number of calibration lines provides better sensitivity estimation and reconstruction performance.

Brain MPRAGE data was collected at a matrix size of 256 x 256 x 176, at full sampling. Multislice images were obtained by Fourier transforming in the z direction, and then the slices were individually undersampled by throwing away 3 out of 4 lines in k_y direction for each slice. Calibration views were treated separately according to the scheme described above. Sensitivity estimation was then carried out by polynomial fitting of the multislice view-shared calibration data to a 4th order polynomial.

RESULTS

Fig 3 shows reconstructions for 4-fold acceleration using both 2D SENSE and 3D phase constrained graph cut (PC-EPIGRAM). Notice significant noise amplification in SENSE which could not be removed using higher regularization, effectively eliminated by proposed 3D spatial prior. Reconstruction of a 256 x 256 x 176 volume currently takes around 1 hour on a 2.9 GHz P4 machine. We chose regularization parameter of 0.1 for both SENSE and EPIGRAM, 8 iterations of EPIGRAM loop. Quantitative results on 6 data sets is shown in table 1, following technique of [2].

Table 1: Mean SNR and g-factor (noise amplification) for 6 MPRAGE cases

SENSE SNR	SENSE g-factor	EPIGRAM SNR	EPPIGRAM g-factor
19.2	3.1	36.4	1.3

DISCUSSION

We have demonstrated improved performance using 3-D edge preserving spatial priors compared to 2-D priors used in [2,3]. Preliminary results suggest some exciting 3-D fast imaging applications. Future work will focus on higher accelerations and improved processing speed.

REFERENCES

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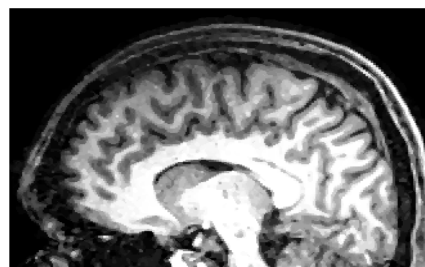
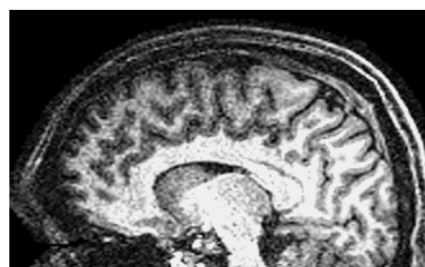
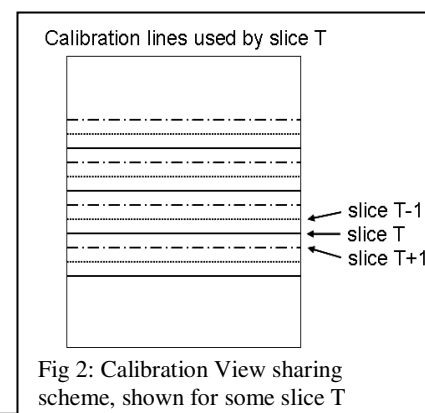
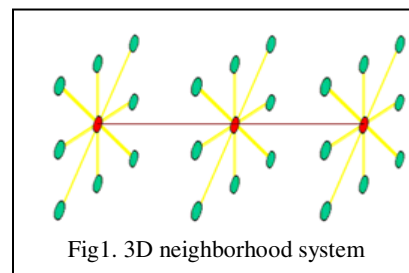


Fig 3: Reconstruction on MPRAGE data, 4x acceleration