Edge Preserving Bayesian Reconstruction Method for Parallel Imaging and Application in Cadiac MRI

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INTRODUCTION

The parallel imaging process leads to a drop in signal to noise ratio (SNR) that makes image interpretation difficult. Regularization based reconstruction methods use prior information about the underlying target to improve the quality of image. Standard regularization methods assume that the underlying image is globally smooth, but images have sharp edges and are piecewise smooth. Therefore standard methods like Tikhonov regularization [1] cause excessive blurring at the edges in an image. The challenge to improving SNR without blurring occurs in other areas like image denoising and stereo vision where edge preserving priors based on Markov Random Field (MRF) property are used. Edge preserving MRF priors make Bayesian estimation a non convex optimization problem for which finding a good solution is time intensive. Here we propose a Bayesian reconstruction method based on a fast graph cuts algorithm [2] that improves SNR while preserving sharp edges. The proposed method performs better than the standard SENSE method [3] and is faster than other edge preserving Bayesian methods [4]. Reconstruction results at reduction factors of 2, 3 and 4 are compared against SENSE for different cardiac applications.

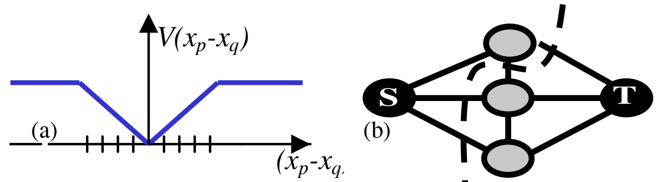

Fig.1 (a) Edge preserving prior: Truncated L1 Distance (b) In the graph nodes correspond to pixels and edges represent weight associated to pixels in different energy terms. A minimum cut solves binary minimization problem, which is repeated over set of given labels.

METHOD

The cartesian parallel imaging problem can be reduced to minimization of an energy function $E(x) = \| y - Sx \|^2 + \sum_{(p,q)\epsilon N} V(x_p, x_q)$ to find the Bayesian estimate of the underlying image. Here V is a truncated linear penalty function (Fig. 1a) that encodes edge preserving piecewise smooth priors, x is the target image, y is coil outputs and the S matrix captures the sensitivities of different coils [4]. We use a fast routine based on a graph cuts jump move algorithm [5] to minimize $E(x)$ by successively finding the minimum energy solution of a binary optimization problem (Fig. 1b) over the set of labels $S = [-2^{m-1}, -2^{m-2} \ldots 2^{m-2}, 2^{m-1}]$ where $m = \log_2$ (max *Intensity*).

Bayesian cardiac MRI was performed on 5 subjects. Coronary artery imaging was performed using an ECG-triggered segmented k-space navigator gated SSFP 3D coronary MRA pulse sequence. Cine gradient echo scans were acquired along the short axis at the mid-ventricular level and in a four-chamber view. Short axis cardiac black blood images were obtained using a free breathing navigator gated double inversion recovery prepared black blood fast spin echo sequence. Delayed enhancement imaging was done with T1 weighted gradient echo pulse sequence using standard imaging parameters. The blood SNR is measured using the method as described in [4, 6].

RESULTS

Cardiac MRI and Bayesian reconstruction were successfully performed on all the subjects. Fig. 3a1, 3a2 show coronary artery imaging reconstruction using SENSE and Graph Cuts at reduction factor R=3; the Graph Cuts reconstruction improved SNR over the SENSE reconstruction in blood pool by 60% ± 11% and in myocardium by 62% ± 13% on average over 5 subjects. Fig. 3b1 & b2 show SNR improvement for short axis cardiac black blood images at R=2. Fig. 3c1, c2 show noise reduction in a case of short axis cine image at R=4, and Fig. 3d1, d2 show the same for delay enhanced cardiac imaging at R=2. Reconstruction of a 256x256 resolution image with 512 intensity levels at R=3 takes less than a minute on 2.66 GHz P4 machine.

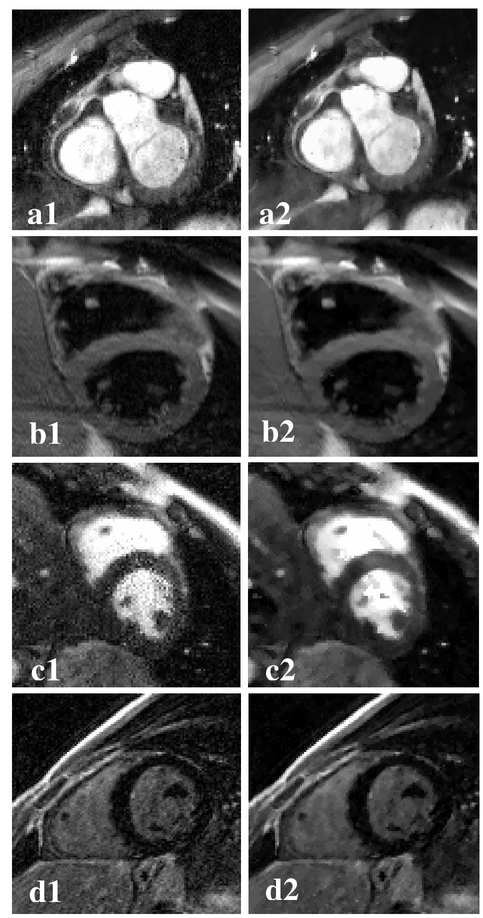

Fig. 3 Right Coronary Artery reconstructed at R=3 (a1) SENSE (a2) Graph Cuts. Black blood short axis cardiac image reconstructed at R=2 (b1) SENSE (b2) Graph Cuts. Short axis cine image reconstructed at R=4 (c1) SENSE (c2) Graph Cuts. Delay enhanced cardiac imaging at R=2 (d1) SENSE (d2) Graph Cuts.

DISCUSSION

We have demonstrated improvement in SNR is achieved using edge preserving Bayessian reconstruction for high acceleration parallel imaging in cardiac applications. Future work will focus on combination of acceleration in temporal and spatial domain.

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