High Quality Iterative Image Reconstruction For Multi-Slice Helical CT

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***Abstract*— Imaging from multi-slice CT data is of particular interest for its clinical relevance in diagnostic purposes, but suffers from the difficulty of appropriately handling cone-beam geometry, high pitches, and low dosage. In this paper, we develop and investigate the performance of iterative reconstruction algorithms in order to compare image artifacts with conventional methods, as an attempt to improve image quality. We demonstrate the feasibility of such techniques by adapting existing Bayesian imaging methods to reconstruction from pre-corrected multi-slice helical CT data, which leads to the first original comparison between Filtered Back-Projection (FBP) and iterative reconstruction in a three-dimensional setup similar to that of a real clinical acquisition.**

I. Introduction

Demands for new clinical applications in CT diagnostic imaging have pushed manufacturers to develop scanning techniques resulting in faster acquisition and larger coverage through the use of multi-slice detectors, faster rotation speeds, and high helical pitches. The large coverage and increased spatial resolution of the detector array makes multi-slice CT very attractive for clinical applications, enabling shorter acquisition times and thinner slices. As the number of slices increases, however, the geometry of the projections evolves into a three-dimensional space instead of the two-dimensional space where application of conventional methods of reconstruction is appropriate. High-pitch helical scanning is particularly desirable when combined with multi-slice detectors as it decreases acquisition time, but it further increases the deviation from conventional two-dimensional planar data. Current state-of-the-art reconstruction algorithms generally require a closed form formulation, and try to address cone-beam artifacts by doing forms of three-dimensional filtered back-projection [1], or by implementing complex view weighting techniques to achieve superior image quality [2]. They are faced with the challenge of dealing with inaccuracies inherent to the interpolation of the helical data to approximate the measurements that would be made from an equivalent plane of acquisition.

While much effort is devoted to the improvement and implementation of these analytical reconstruction methods because of their computational efficiency, iterative techniques and their benefits for this application have so far not been fully investigated. Although they require many more operations, they offer the potential to produce reconstructions with substantially reduced artifacts through the inclusion of non-idealities in the problem description. Rather than treating all measurements with equal weighting, a statistical model allows differing degrees of credibility among data. This advantage of robustness of statistical methods over conventional reconstruction methods is particularly worth mentioning: helical view weighting in FBP is very sensitive to inaccuracies, and small perturbations in the computation of the weights or their application to the data may result in significant degradation of image quality, which may prove a difficult challenge for practical implementation. Rather than manipulating data to force it to conform to a format suited for direct reconstruction methods, statistical methods attempt, to the degree possible, to explicitly include data non-idealities in the problem description.

Direct methods also cannot include image models with sufficient generality to describe realistic medical imagery. Limitation to sinogram-domain correction and pre-processing prevents the use of modern stochastic image models in conventional reconstruction. These problems are made more severe if the dosage levels are reduced, as desirable in many applications. In iterative reconstruction, constraints such as positivity or spatial smoothness can be enforced to increase the quality of the reconstructed image in various ways.

Because of the sheer dimension of the inverse problem and of the alleged computational complexity of their implementation, there is a tendency to believe that statistical iterative methods are ill-suited to practical reconstruction of multi-slice helical CT data, which is the standard on current medical diagnostic scanners. Allain, Idier, *et al*, [3] investigated an iterative regularized approach for helical data that describes some practical implementation issues, but their work applies to single-slice only. We generally find that the problem of iterative reconstruction for multi-slice CT helical data has been overlooked in the literature. In particular, there has been no comparison between images reconstructed both with iterative techniques and state-of-the-art conventional methods with the dimensions of a clinical setup. For these reasons, we devote here some efforts toward, to our knowledge, the first comparison between FBP and iterative reconstructions from three-dimensional multi-slice helical data.

II. Statistical Reconstruction From Multi-Slice Helical CT Data

Consider the corruption of measurements by counting statistics in low dosage cases. Rather than treating all measurements with equal weighting, a statistical model allows differing degrees of credibility among data. Let $\mathbf{y}$ be the measurement data, and let $\mathbf{x}$ be the unknown image to be reconstructed. In general, there will be a matrix A such that $E[\mathbf{y}] = \bar{\mathbf{y}} \approx \mathbf{Ax}$ where $\bar{y}$ is the noise-free value of the measurement, and $E[y]$ indicates the statistical average of the data y. Statistical reconstruction methods generally work by finding a solution to the problem

$$\min_x \left[\sum_i d_i \left(y_i - [Ax]_i \right)^2 + U(x) \right] \tag{1}$$

where d_i may reflect the inherent variation in credibility of data, and $U(x)$ is a regularization term which encourages smoothness in the solution. For example, if a particular measurement is photon-starved by some highly attenuating object, a problem which may cause artifacts in conventional images, a statistical reconstruction simply assigns low weight to any errors associated with that measurement by reducing the corresponding d_i. The regularization term $U(x)$, a feature of Bayesian image estimation, adds a penalty to behavior reconstructed in the image x which might be highly atypical. This penalty, normally extremely simple, is meant only to encourage the state in which neighboring entries in the image have similar values. Optimization of the expression in (1) requires iterative methods which are generally more computationally expensive than direct reconstruction.

The crucial advantage of statistical image reconstruction in this framework is that it allows any choice of the matrix A to describe the imaging system. Any scanning geometry can be accurately modeled by proper computations of the entries of the matrix A, often referred to as the "forward projection" matrix. The forward model can be designed to be as close as possible to reality, although this may come at the cost of great computational expense. FBP is feasible primarily in systems in which A describes uniformly spaced, closely sampled data. Statistical methods have an advantage in having little dependence in their implementation on the geometry of data collection. The optimization of (1) is attacked in the same manner regardless of the scan pattern represented by A. The problem lies in determining the elements of A that describe the contribution of any measurement data to any element of the reconstruction space. Because it is necessary to include the non-planar character of the measurements of the helical scan into the forward model, the computation of the elements of A must be done in the three spatial dimensions. This computation is a fundamental component to our approach. It requires software retracing of the slices of the scan during reconstruction in order to calculate the interaction between volumetric elements of reconstruction with X-rays at arbitrary angles in three dimensions. A crude but workable model involves the calculation of the intersection between scanner rays and voxels in the reconstruction space. Although the calculations involved may not be trivial, there is no fundamental problem in describing it exactly in A for the statistical methods.

The regularization term $U(x)$ enforces smoothness in the reconstructed images, independently of the formulation of the forward model. Its parameters provide another level of control over the noise and resolution of the final image estimate. In order to account for interdependence of the neighboring planes in the three-dimensional acquisition volume, the formulation of the regularization must include all the neighbors of a given element in the three-dimensional space. The Generalized Gaussian Markov Random Field (GGMRF) [4] represents a simple formulation of the prior term with the desired effect:

$$U(x) = \frac{1}{q\sigma^q} \sum_{\{j,k\} \in C} b_{j,k} |x_j - x_k|^q \tag{2}$$

where C is the set of all neighboring pixel pairs in three-dimensions, and σ is a measure of the standard deviation of the noise in the measurements. Equation (2) ensures that sharp edges are increasingly well preserved as the exponent $1 \leq q \leq 2$ decreases, and maintains the desirable convex nature of the overall problem formulation.

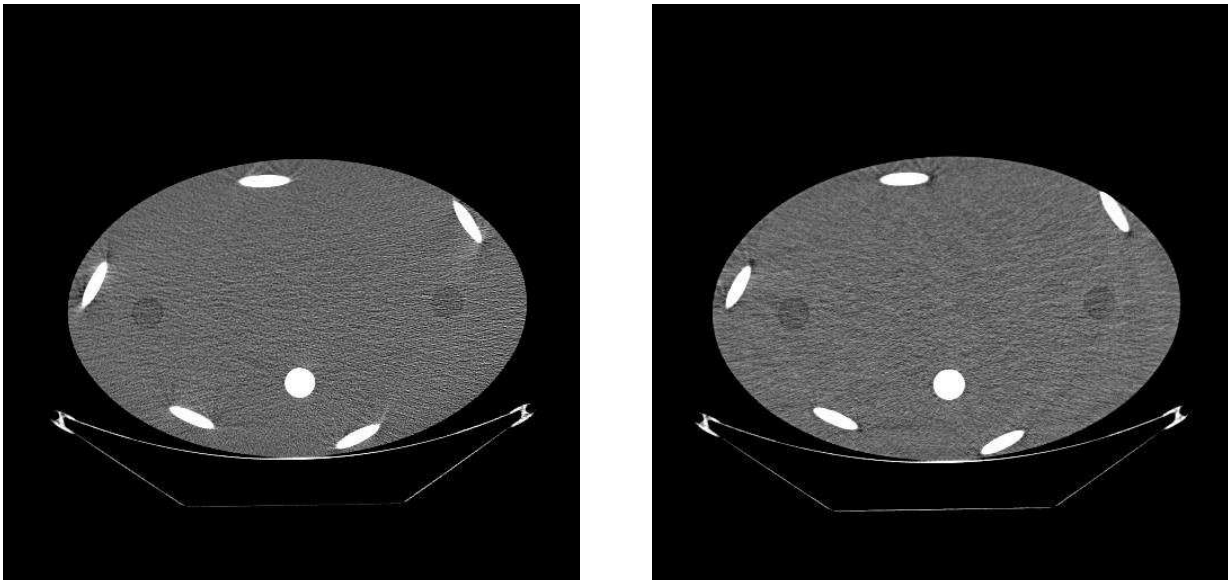
III. Solution of the Optimization Problem

The computational problem of statistical image reconstruction is that of optimizing an estimate $\hat{x}$ of the three-dimensional reconstruction space against a functional including a statistical measure of the difference between the estimated forward projection space and the true measurements, as well as the regularization term (2):

$$\hat{x} = \arg\min_{x \in \Omega} \left[\sum_i d_i \left(y_i - [Ax]_i \right)^2 + \frac{1}{q\sigma^q} \sum_{\{j,k\} \in C} b_{j,k} |x_j - x_k|^q \right] \tag{3}$$

where Ω can be chosen as the convex set of positive reconstructions to describe the physical nature of the image space.

Optimization over the full 3D volume may be attacked by iteratively visiting each voxel of the reconstruction space. Sequential voxel updates are calculated using Iterative Coordinate Descent (ICD) [5], which has shown rapid convergence in other tomographic problems. Greedy updates of voxel values may be computed directly in the purely quadratic case of the Gaussian prior model, but require a one-dimensional line search for other cases of the GGMRF such as the edge-preserving model of $q \gtrapprox 1$ in (2). While the cost of these iterations remains high relative to FBP, a full 3D reconstruction typically converges in fewer than 20 iterations.



(a) (b)

Fig. 1. Rib phantom reconstructions using helical scan data with normalized pitch 1.675:1 at 1.25 mm detector collimation, 0.5 second per rotation, 120kV, 320 mAs, with a window width of 300 and level of 0. Reconstructions performed using (a) helical view weighting FBP; (b) Iterative reconstruction with q=2.0; $\sigma = 10$. Iterative reconstruction has comparable quality to FBP reconstructions with increased artifacts in some areas and reduced artifacts in others.

IV. Results

The following reconstructions result from multislice helical scan data acquired at 0.5 second rotation speed, 1.25 mm detector collimation, with 984 views per rotation, and pitch of helical scan adjusted for minimum complete coverage. The 3D reconstruction includes all image planes intersected by one full rotation of the gantry. Planes are separated by 1 mm in the results shown here. Figure 1 uses an oval phantom with Teflon simulated ribs to compare the quality of helical view weighting FBP to the current iterative reconstruction algorithm using a Gaussian prior model. The resulting iterative reconstruction has comparable or slightly better quality than the FBP reconstruction, with reduced helical artifacts in some locations and increased artifacts in others.

Figure 2 uses a GE Performance phantom with little variation in the z direction in an attempt to look specifically at the performance of the iterative method in terms of spatial resolution. The quality of the FBP reconstruction is therefore essentially equivalent to that of a purely axial scan. The iterative reconstruction algorithm uses a non-Gaussian prior model with greater tolerance for sharp edges. Table I gives the tabulated values of the 50% modulation transfer function (MTF) and noise computed in the reconstructions, and Fig. 3 shows a windowed portion of the two reconstructions used in MTF computations. In this case, the iterative reconstruction has significantly better resolution with slightly reduced noise as compared to the FBP reconstruction.

TABLE I

MTF and noise evaluation for GE Performance phantom reconstructions using (a) FBP reconstruction; (b) Iterative reconstruction with $q = 1.1$; $\sigma = 25$.

	FBP Recon	Iterative Recon
50% MTF (lp/cm)	4.44	8.21
Noise std. dev. (water)	11.02	9.35

V. Conclusion

Preliminary results shown here demonstrate that Bayesian iterative methods may offer significantly improved resolution at comparable noise level, and artifact suppression in helical scan X-ray CT, at the cost of increased computation. Such a performance-cost tradeoff appears valuable for the reconstruction of high pitch and/or low SNR helical scan data.

References

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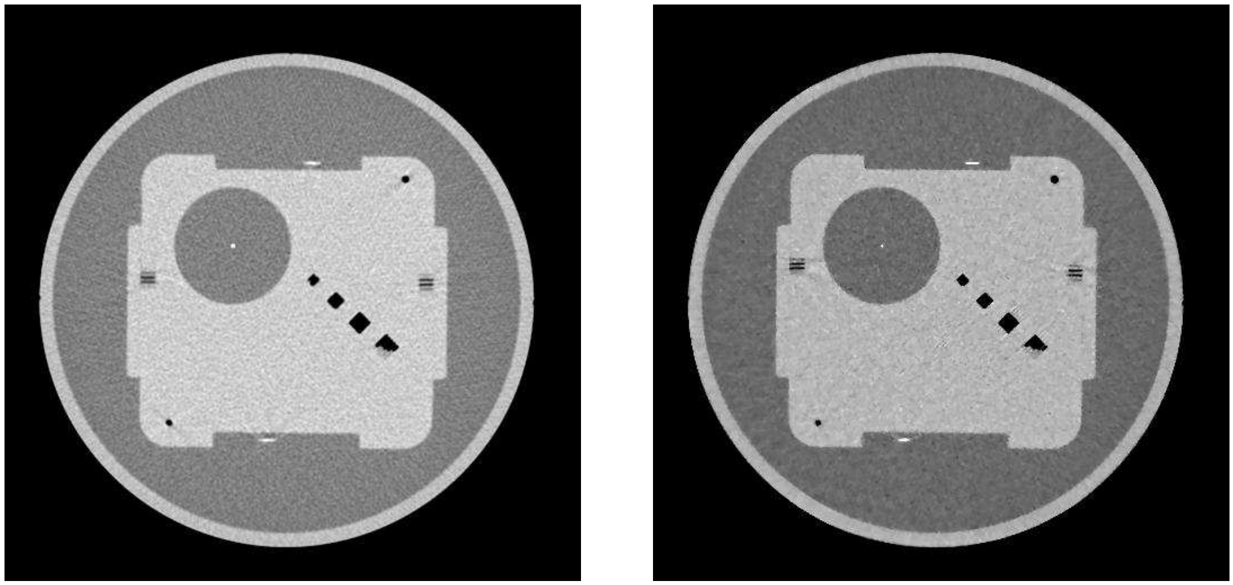

(a) (b)

Fig. 2. Reconstructions of GE Performance phantom obtained using (a) FBP; (b) Iterative reconstruction with q=1.1 and $\sigma = 25$ with a window width of 300 and a level of 0. Iterative reconstruction with non-Gaussian image model produces significantly higher resolution than FBP with slightly reduced noise. (See Table I.)

(a) (b)

Fig. 3. Windowed versions of GE Performance phantom region used to compute MTF performance estimates (window level 600). Two images show reconstructions using (a) helical view-weighted FBP reconstruction; (b) Iterative reconstruction with q=1.1; σ=25.