ALGEBRAIC RECONSTRUCTION OF ULTRAFAST TOMOGRAPHY IMAGES AT THE LARGE SCALE DATA FACILITY*

Xiaoli Yang†, Thomas Jejkal, Rainer Stotzka, Halil Pasic, Tomy dos Santos Rolo
Thomas van de Kamp, Achim Streit, Karlsruhe Institute of Technology, Karlsruhe, Germany

Abstract

The ultrafast tomography system built up at the ANKA Synchrotron Light Source at KIT makes possible the study of moving biological objects with high temporal and spatial resolution. The resulting amounts of data are challenging in terms of reconstruction algorithm, automatic processing software and computing. The standard and manually operated reconstruction method yields limited quality of reconstruction images due to much fewer projections obtained from the ultrafast tomography. Thus an algebraic reconstruction technique based on a more precise forward transform model and compressive sampling theory is investigated. It results in high quality images, but is computationally very intensive. For near real–time reconstruction, an automatic workflow is started after data ingest, processing a full volume data in parallel using the Hadoop cluster at the Large Scale Data Facility (LSDF) to reduce the computing time greatly. It will not only provide better reconstruction results but also higher data analysis efficiency to users. This study contributes to the construction of the fast tomography system at ANKA and will enhance its application in the fields of chemistry, biology and new materials.

INTRODUCTION

In the field of computed tomography (CT), sparse reconstruction has been becoming a critical topic, which discusses how to estimate an accurate tomographic image if the projection data are not theoretically sufficient for exact image reconstruction according to the Nyquist-Shannon sampling theorem. The insufficient data problem occurs in the case of ultrafast tomography, which is currently under construction at ANKA [1], the synchrotron light source located at Karlsruhe Institute of Technology (KIT). The system has basically two main advantages in the study of moving biological objects. First, the objects can be regarded as static during the imaging process due to the fast scanning mode, which correspondingly minimizes the effects of the movements on reconstruction accuracy. On the other hand it highly reduces the radiation dose so that the lifetime of biological objects increases for longer–time scientific studying. However fewer projections in the range of 180 degrees are actually obtained from the fast tomography system due to the high rotation speed of objects, and the application of standard analytic algorithm for insufficient projection data such as filtered back-projection (FBP) [2] will lead to conspicuous artifacts in reconstruction images.

The algebraic reconstruction techniques (ART) [2] are the widely used iterative reconstruction algorithms recently due to its great advantages in integrating the prior knowledge to the reconstruction process. However the linear inverse problem becomes ill-posed due to too less measurements. Inspired by the compressive sampling (CS) theory [3], the tomographic reconstruction from incomplete projection data is believed to have an exact solution in some sparse transform space, such as the gradient space of the underlying image. As a result, Total Variation (TV)–based algorithms obtain high popularity in image restoration [4]. Emil Y. Sidky et al. firstly introduced the concept of TV into CT reconstruction considering the sparse distribution of the gradient of source image and developed a new algorithm TV-POCS in 2006 [5]. It performs a TV minimization by the gradient descent method after each SIRT (Simultaneous Iterative Reconstruction Techniques) iteration for sparse reconstruction of incomplete projection data. Later in 2008, Sidky et al. updated the algorithm to the steepest descent method with an adaptive stepsize called ADS-POCS for TV minimization improving the reconstruction robustness against the cone-beam artifacts from sparse reconstruction [6].

In more general applications of signal denoising and restoration, CS theory has been studied a lot in order to restore the original signal from sparsely measured data. It happens to hold the same view that TV norm is used as the popular regularization for sparse image restoration. Different from these algorithms TV-POCS, ADS-POCS of CT reconstruction, it integrates the TV norm into the data consistency constrains forming one minimization program. The original sparse signal is restored by solving this minimization program with the TV regularization. Several TV solvers have been publicly available such as L1-Magic [3], TwIST [7], NESTA [8], RecPF [9] and TVAL3 [10]. In this paper TVAL3 is integrated to the ART framework to perform the reconstruction of the real experiment data. It shows high reconstruction quality and will be denoted as CS–ART algorithm for tomography reconstruction.

Even though CS–ART algorithm proves high quality reconstruction images, it is known as a time intensive method in comparison with the standard method FBP and a parallel computing architecture is required. The Large Scale Data Facility (LSDF) [11], located on the same campus as

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† Institute for Data Processing and Electronics (IPE), KIT, Germany. Email: xiaoli.yang@partner.kit.edu

ANKA is not only a distributed storage facility supporting data storage and management, but also connected to a Hadoop [12] cluster for parallel data processing. In this paper, we will focus on the parallel computing of 3D tomography reconstruction and reports its promising computing performance. It is also a significant part of the designed workflow of LSDF for automatic data analysis of ANKA.

CS–ART RECONSTRUCTION METHOD

For tomography reconstruction, a forward model describing the imaging process must be defined firstly to erect the inverse problem. Usually a straight line or a fat line is used to model the X–ray going through the object area [2]. In this section, we will use a more precise ray model for X–ray tomography forward model and then discuss the algorithms for solving the established inverse problem.

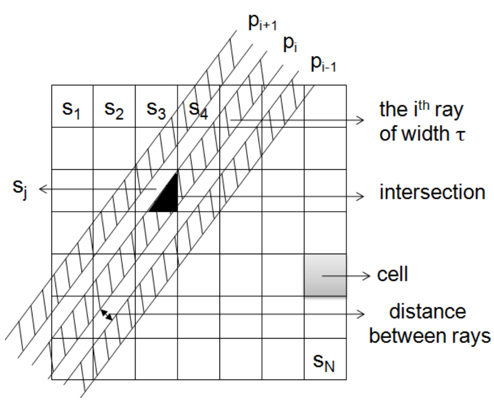

Figure 1: Forward model for ART methods.

ART Forward Model

Taking the sensor geometry into account, it is more appropriate to describe the rays as having a finite width and a given distance. Therefore, a new ray model in ART possesses two features: 1) a ray is of a certain width τ; 2) a distance exists between the neighbor rays. To illustrate this, shaded rays are shown in Fig. 1. Generally, ART assumes that the cross section of the object consists of an array of unknowns representing the X–ray absorption coefficients of the object, denoted by $s_j, (j = 1, 2, \ldots, N)$. The intersection area represents the contribution of image cell s_j to the i^{th} ray projection. It is expressed as a factor a_{ij} equal to the ratio of intersection and cell area. Let p_i be the projection measured with the i^{th} ray which equals

$$p_i = \sum_{j=1}^{N} a_{ij} s_j, \quad i = 1, 2, \ldots, M, \tag{1}$$

where M is the total number of rays. The linear equation system (1) can be simply written as a matrix form $p = \mathbf{A}s$, where $s = \{s_1, s_2, \ldots, s_N\}$ is the image vector; $p = \{p_1, p_2, \ldots, p_M\}$ is the set of all measured projections.

Reconstruction Method

The purpose of the reconstruction algorithm is to obtain the original object s from the observations p by solving the discrete linear equation system (1). However, in the case of incomplete projection data, the linear system is an ill-posed problem. To produce reasonable solutions, the TV algorithms are to incorporate the assumption of gradient image sparseness on the image function s to arrive at a solution from data p, which actually implement the following optimization program:

$$\min \ \|s\|_{TV}, \quad \text{such that } \ p = \mathbf{A}s, \tag{2}$$

where $\|s\|_{TV}$ is defined as:

$$\|s\|_{TV} = \sum_{m,n} \| \nabla s_{m,n} \| = \sum_{m,n} G^s_{m,n} \tag{3}$$

$$G^s_{m,n} = \sqrt{(s_{m,n} - s_{m-1,n})^2 + (s_{m,n} - s_{m,n-1})^2}. \tag{4}$$

The program (2) is commonly performed in two steps [5, 6]: (1) SIRT iteration for data consistency, and (2) TV descent iteration for reasonable solution. In the context of tomography reconstruction, the optimal solution is achieved by repeat these two steps alternately until the convergence condition is fulfilled. Another possibility to perform the TV algorithm is considering the TV term as a regularization in a cost function without any constrains and reform the minimization program as the following

$$\min \ \|p - \mathbf{A}s\|_2^2 + \lambda \|s\|_{TV}. \tag{5}$$

It is a general form of inverse problem in the field of sparse signal restoration taking into account the data consistency and TV minimization meanwhile. λ is the tradeoff parameter to control the balance between these two terms. The bright side of performing this kind of program is that some mature solvers have been available to solve the probelm as mentioned in the section of introduction. They can be incorporated into the reconstruction framework without need to change too much codes. The robustness of reconstruction image and convergence rate are the critical properties of concern. TVAL3 is a “Total Variation Minimization by Augmented Lagrangian and Alternating Direction Algorithms”, proposed to handle the optimization problems resulting from some linear inverse problem with TV regularization. It exhibits fast convergence rate and meanwhile keeps the robustness of the resulting images. In this paper, the TVAL3 solver is incorporated with the forward model introduced in the previous section, which will be denoted as CS–ART method.

The CS–ART method is used to reconstruct the real biological data set (fast tomography of a weevil) and shows high quality reconstruction image as Fig. 2. The reconstruction results of one slice are compared. Figure 2(a) is a referenced reconstruction image which is obtained from 1500 projections by FBP algorithm. Figure 2(b) is the reconstructed image from a sub-set, 60 projections of 1500,

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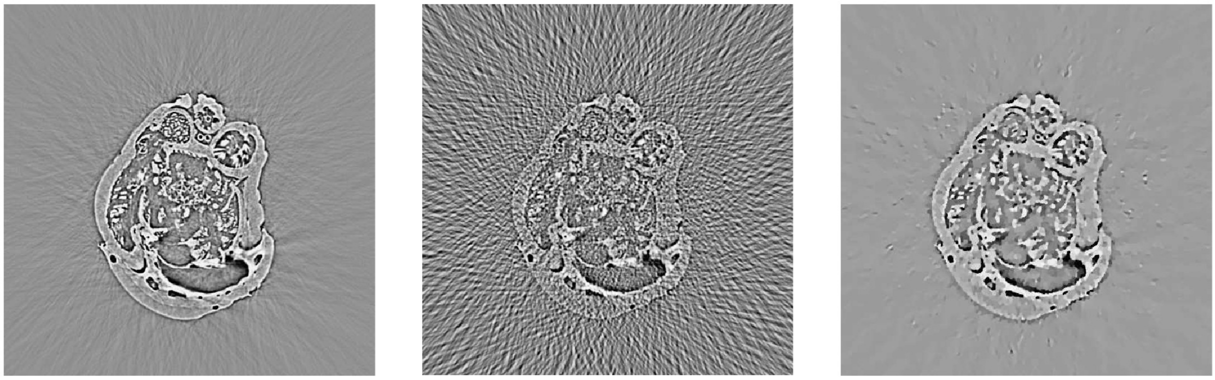

(a) (b) (c)

Figure 2: Reconstruction result comparison: (a) is the reference image from 1500 projections constructed by FBP; (b) is reconstructed from the sub–data set, 60 projections, by FBP and shows serious artifacts and streaks; (c) shows the reconstructed image by the CS–based ART method from the same 60 projections.

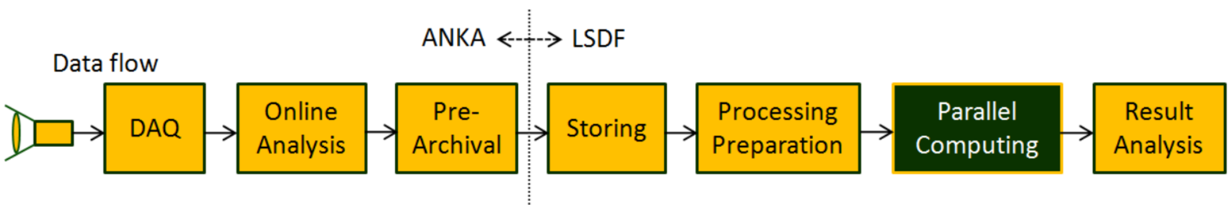

Figure 3: Automatic data processing workflow of LSDF for data analysis of ANKA tomography beamline TOPO–TOMO/IMAGE.

showing serious artifacts and streaks. The third reconstruction image, displayed in Fig. 2(c) is reconstructed from the same sub-data set as (b), but uses the CS–based ART algorithm, which reduces the artifacts a lot and is similar to the reference image in quality assessment.

PARALLEL RECONSTRUCTION AT THE LSDF

The LSDF is designed to cope with the increasing requirements of data intensive scientific experiments. Currently, data management and analysis at ANKA are still performed manually. Thus, a workflow of LSDF is designed as Fig. 3 for automatic data analysis of ANKA in the near future. The part of parallel computing is discussed in this section.

Data Parallel Reconstruction with CS–ART

Even though CS–ART algorithm proves high quality reconstruction images, it is known as a time intensive method in comparison with the standard method FBP. The sequential implementation of a full volume reconstruction will take tens of hours. Thus, a parallel computing architecture is required for 3D tomography reconstruction. It is quite straightforward to implement the data parallel reconstruction at LSDF cluster.

As shown in Fig. 4, the 3D experimental data mentioned above consists of 1024 slices. Each of them will be reconstructed by the same algorithm of CS–ART. With the

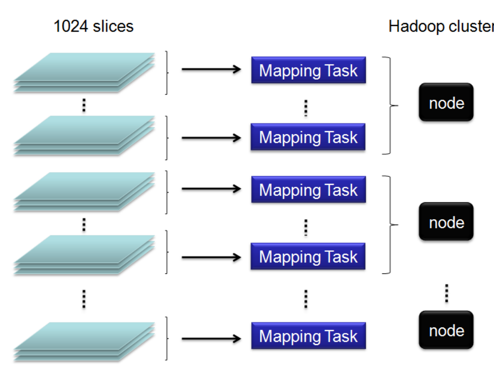

Figure 4: Data parallel computing for 3D computed tomography reconstruction.

MapReduce framework of Hadoop [12], the whole reconstruction job is able to be distributed to computer nodes of the cluster. In our implementation, 37 nodes in the Hadoop cluster are available. Each node in the cluster has the ability to process up to six mapping tasks and two reducing tasks in parallel, which is set in Hadoop as a compromise between task size and number of cores being used. Thus, we divide the whole job, 1024 slice reconstructions, into a number of mapping tasks, which are afterward distributed to different nodes automatically by Hadoop. Each mapping task handles a similar number of slices sequentially, but the executions in each node for different mapping tasks are parallel.

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Table 1: Times Recorded for Parallel Reconstruction Job

Parallel Tasks n	**Time (s)**	**Speedup**
1	39727	–
12	3415	11.63
24	1747	22.73
37	1107	35.85
74	650	61.08
111	488	81.39
148	417	95.20
185	360	110.2
222	330	120.0

Reconstruction times in seconds are recorded directly on the number of parallel tasks. They are shown in Table 1 The first line gives the time for sequential implementation. From the times, the speedup factors are also given to evaluate the performance of parallel computing. It is defined as the division of sequential implementation time by the parallel time. As the number of parallel tasks increases from 12 to 222, the time needed for a 3D reconstruction job decreases rapidly to 330 seconds, which is less than 6 minutes. Meanwhile the speedup factor goes up to 120. It suggests that the 3D reconstruction of the experimental data can be finished in a near instantaneous time with the parallel computing architecture at LSDF.

DISCUSSION AND CONCLUSION

In this paper, sparse reconstruction in the application of ultrafast CT is discussed. It happens frequently due to the need of reducing X–ray radiation dose or some limitations of imaging device and experimental condition. The insufficient data appear in case of ultrafast tomography because of its fast rotation to reduce the imaging time. Even though the insufficient data for exact reconstruction using the standard method, TV–based algorithm still shows promising reconstruction results based on the CS theory compared with the conspicuous artifacts of the FBP method. In this paper, TVAL3 algorithm based on the TV is incorporated into our framework of sparse CT reconstruction with the precise forward model, denoted as CS–ART algorithm, showing promising reconstruction results and fast convergence rate.

In this paper, the data parallel computing method for a full volume tomographic reconstruction is also discussed. With the Hadoop cluster at the LSDF, data parallel computing of 3D CT reconstruction is performed by distributing the reconstruction job into a number of parallel tasks. Compared with the sequential reconstruction taking more than ten hours, the parallel computing using 37 nodes at the LSDF only needs less than 6 minutes with the speedup factor reaching up to 120. The parallel computing part completes the LSDF workflow for automatic data analysis. So the workflow will highly enhance not only the data storage but also the data analysis efficiency.

The promising reconstruction image and high computing performance demonstrate the effectiveness of LSDF in processing big experimental data from the tomography beamline of ANKA. In the near future, the reconstruction framework will be integrated into the LSDF workflow to improve the data analysis efficiency and provide results to users in nearly instantaneous time. This is a critical building block on the way to construct the fast tomography system at ANKA.

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