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Limited view X-ray tomography for dimensional measurements

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A B S T R A C T

The growing use of complex and irregularly shaped components for safety-critical applications has increasingly led to the adoption of X-ray CT as an NDE inspection tool. Standard X-ray CT methods require thousands of projections, each distributed evenly through 360° to produce an accurate image. The time consuming acquisition of thousands of projections can lead to significant bottlenecks. Recent developments in medical imaging driven by both increasing computational power and the desire to reduce patient X-ray exposure have led to the development of a number of limited view CT methodologies. Thus far these limited view algorithms have been applied to basic synthetic data derived from simple medical phantoms. Here, we use experimental data to rigorously test the capability of limited view algorithms to accurately reconstruct and precisely measure the dimensional features of an additive manufactured sample and a turbine blade. Our findings highlight the importance of prior information in producing accurate reconstructions capable of significantly reducing X-ray projections by at least an order of magnitude. In the turbine blade example a dramatic reduction in projections from 5000 to 24 was observed while still demonstrating the same level of accuracy as standard CT methods. The findings of the study also suggest the importance of sample complexity and the presence of sparsity in the X-ray projections in order to maximise the capabilities of these limited algorithms. With the ever increasing computational power, limited view CT algorithms offer a method for reducing data acquisition time and alleviating manufacturing throughput bottlenecks without compromising image accuracy and quality.

1. Introduction

Modern engineering is increasingly utilising complex components. Turbine blades, for example, feature complex cooling channels and highly optimised curved surfaces, and the rise of additive manufacturing has given huge potential for extremely complex shapes. Such shapes present significant inspection challenges to traditional NDE techniques, as these features can obscure defects or manufacturing errors. X-ray computational tomography (CT) is one of the few technologies capable of non-destructively measuring both the external and internal features of a component [1]. Numerous CT approaches exist, but within industry they commonly consist of a static X-ray source and a movable detector which is perpendicular to the source. The sample to be CT scanned is placed on a movable disk which rotates through 360° allowing multiple X-rays projections to be captured. Standard X-ray CT methods require thousands of projections, each regularly and evenly distributed through 360° to produce an accurate image [2,3]. Once an accurate tomographic image is generated it can be used to assess the specimen for flaws, quality control and undergo dimensional analysis by comparison with CAD e.g., [1].

One of the major downsides of X-ray CT is the time consuming data acquisition process which can lead to significant bottlenecks. To alleviate these bottlenecks in throughput, companies may be forced to purchase additional X-ray CT capability at great cost or reduce individual X-ray exposure times lowering the signal-to-noise rato and image quality. Spurred by the ever increasing power of computers and the increasing flexibility of graphics cards for general purpose computing [4], a variety of limited view tomographic techniques capable of generating high quality images with less data have been developed for medical purposes e.g., [5–13]. Although much theoretical work has been conducted over the past decade on limited view tomography the algorithms developed have been tested on simple synthetic examples (e.g., Shepp - Logan phantom [2]) typically with parallel ray geometry, which poorly mimics true industrial applications where ray path geometries and noise are an issue.

Routine medical X-ray CT applications are limited to disease or trauma detection and the precise measurements are often not required as

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other, higher resolution and targeted, diagnostics methodologies (e.g., MRI) may be applied. In contrast, industrial CT requires precise high resolution and high contrast images to provide meaningful dimensional measurements for quality control purposes. These differences in the objectives of medical and industrial X-ray CT may prevent the direct transfer of the newly developed imaging algorithms. Here we survey and quantify the performance of limited view tomographic algorithms developed for medical applications to reconstruct and precisely measure the dimensional features of a turbine blade and a simple additive manufactured sample using industrial X-ray data and setup.

2. X-ray CT theory

Traditionally X-ray tomographic reconstructions are computed using the filtered back-projection approach or its cone beam equivalent the FDK method [2,3]. The main advantages of the filtered back-projection method are its speed of computation, since it relies on the computation of the Fast Fourier Transform and its inverse, and the low computational memory requirements. Despite these advantages the filtered back projection approach does suffer from a number of drawbacks primarily associated with the data acquisition, where many hundreds or thousands of projections that are uniformly distributed over 360° are required to produce accurate reconstructions [2]. The incorporation of prior knowledge (e.g., material properties and geometry) to aid in the reconstruction is usually available in NDE applications but is often difficult to accomplish.

An alternative method to filtered back-projection imaging is to relate the measured projection data to a set of unknown image pixels via a set of algebraic equations [2,10,16]. The measured amplitude of a monochromatic X-ray through an object is given [2] by

$$I = I_0 \exp\left(-\int_r \mu(x,y)\mathrm{d}s\right), \tag{1}$$

where I is the measured X-ray intensity at the detector, I_0 is the intensity of the monochromatic X-ray source and $\int_r \mu(x,y)\, ds$ is the ray-path integral through the object with radiographic attenuation $\mu(x,y)$. Equation (1) maybe discretised and re-written as

$$-log\frac{I}{I_0} = \sum_{i=1}^{n} a_i \nu_i, \tag{2}$$

where i indicates the pixel number, a_i is the weighting of each pixel based on the length of the X-ray raypaths crossing each pixel and ν is the attenuation value of the pixel. For m observations (2) may be put into matrix form $b = Ax$ where $b \in \mathbb{R}^m$ are the X-ray projections, $A \in \mathbb{R}^{m \times n}$ is a matrix of pixel weights that relates the image to the data projections and

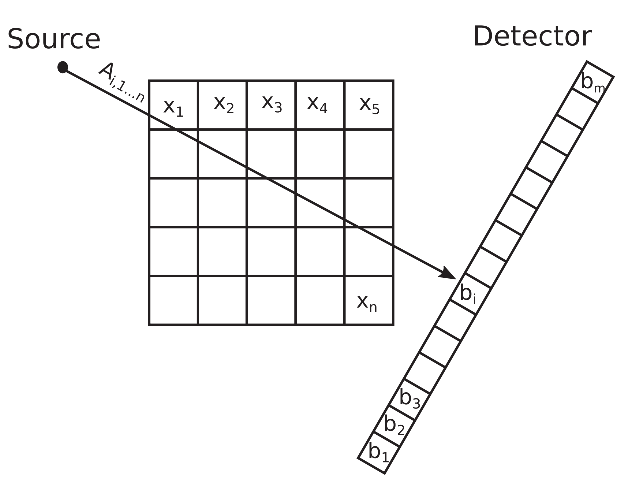

Fig. 1. Illustration of a single ray-path ($A_{i,n}$) passing through a 5×5 pixel image array and recorded on the i^{th} detector bin.

is often called the projection matrix and $x \in \mathbb{R}^n$ are the image pixels (Fig. 1). These systems of equations are usually contaminated by noise, underdetermined and singular and therefore must be solved in a least squares sense [2,10].

The main advantage of formulating the tomographic reconstruction as a least squares inverse problem over the more routinely used filtered back-projection method is its flexibility if large numbers of uniformly sampled data over 360° are unavailable from which to produce an adequate reconstruction [2]. In addition, prior knowledge such as positivity ($x \geq 0$) or the minimum and maximum values of each pixel ($a \leq x \leq b$) may be easily incorporated as constraints. The major downside of the algebraic reconstructions are their relatively slow compute times and solution convergence. However, with the ever increasing power of computers and the advent of graphic card processors the application of least squares inversion for X-ray tomography is rapidly becoming viable, particularly if the acquisition time is reduced by obtaining fewer projections e.g., [5].

2.1. Algebraic tomographic imaging

The system of equations to be solved in CT tomographic imaging are typically large ($n = 262144$ for 512×512 pixel image) so iterative least squares methods must be used to effectively solve the problem [2,10,16]. A series of algebraic reconstruction methods have been developed over the years which iteratively solve the least squares the problem (for example see Refs. [2,16] for a review). Here, we shall consider two routinely applied reconstruction techniques, the Algebraic Reconstruction Technique (ART) and the Simultaneous Iterative Reconstruction Technique (SIRT), which solve the iterative least squares problem by a series of forward- and back-projections.

The ART method is a row action method where the k^{th} iteration of the image is estimated by sweeping through each row of the matrix A and projecting the solution onto orthogonal hyperplanes e.g., [2,16]. These hyperplanes are defined as $b_i - a_i^T x^{[k^{(i-1)}]}$ where b_i is the i^{th} component of the data vector b, a_i is the ith row of A written as a column vector and $x^{[k(i-1)]}$ is the image vector from the $k^{(i-1)}$ iteration. The update to the image vector is computed by orthogonally back-projecting the hyperplane by multiplying it by a_i Practically, the process corresponds to calculating a residual between the measured and the estimated projection made from forward modelling through the current image, then back-projecting this residual to update the image. A single iteration $x^{[k(i)]}$ is completed once the solution has been updated for all rows of A. After each row iteration its prior constraints on the solution such as positivity may be applied. The ART algorithm has been shown to have a convergence history which initially improves the solution to better approximations of the true image but at later iterations diverges away from this. This convergence history is known as semiconvergence and has been shown in the ART case to be very fast obtaining a solution in just a few iterations (Algorithm 1 [16]).

Algorithm 1 Algebraic Reconstruction Technique (ART)

$x^{[0]} = 0$
for k=1, …, K **do**
  for i = 1, …, M **do**
    $x^{[k^{(i)}]} = x^{[k^{(i-1)}]} + \frac{b_i - a_i^T x^{[k^{(i-1)}]}}{\|a_i\|_2^2} a_i$
    ▷ Optional positivity ($x > 0$) or box constraint $x \in [c, d]$
    if pos = True **then**
      if $x^{[k+1]} < 0$ **then** $x^{[k+1]} = 0$
    else if box = True **then**
      if $x^{[k+1]} < c$ **then** $x^{[k+1]} = c$
      else if $x^{[k+1]} > d$ **then** $x^{[k+1]} = d$
  $x^{[k+1]} = x^{[k^{(M)}]}$