Iterative reconstruction in flat panel cone beam tomography for industrial inspection

Jelle Vlassenbroeck¹, Loes Brabant²

¹Inside Matters (inCT bvba), Gentsesteenweg 370, B-9300 Aalst, Belgium, e-mail: Jelle.Vlassenbroeck@insidematters.eu

²UGCT-Department of Physics and Astronomy, Ghent University, Faculty of Sciences, Proeftuinstraat 86, 9000 Ghent, Belgium, e-mail: Loes.Brabant@ugent.be

Abstract

Today, the state of the art in cone beam tomography reconstruction is still based on the FDK algorithm which was originally published in 1984 [1]. However, it has been established that the FDK algorithm has intrinsic shortcomings which cause errors and inaccuracies in the application of flat panel cone beam tomography. Since flat panel cone beam tomography is at present the industry standard for CT inspection of small to medium sized components and materials, there is a clear need to find solutions which overcome these shortcomings.

One of these issues is the presence of cone beam artefacts, which are related both to the incompleteness of the dataset acquired in a circular source-detector trajectory and the approximations in the FDK algorithm. These artefacts can cause inaccuracies when applying CT in metrology, especially for complex parts where sample positioning cannot be fully optimized to prevent the artefacts. Another limitation is the requirement for a complete dataset, including a large number of equiangular projections at a relatively long exposure time. This limits the applicability in imaging dynamic processes and unstable samples where the shape and/or internal structure changes over time (examples can typically be found in food processing). Finally, the approximation of the X-ray interaction process as a simple monochromatic Lambert-Beer determined process results in issues with scattering and beam hardening. These artefacts complicate the inspection of metallic parts produced with additive manufacturing and plastic components containing metal parts encountered in electronics, FMCG, and other industries.

In this study, we investigate the applicability of several iterative reconstruction algorithms to cope with the FDK limitations. These algorithms are more computationally demanding, but are becoming more widely used in medical imaging due to recent progresses in high computing hardware, such as graphics cards, and increased research on the topic in and outside the medical field [2]. We apply these algorithms on industry relevant examples such as metallic components produced with additive manufacturing and polyurethane foams and compare both the computational load and reconstruction accuracy with FDK reconstruction. This study is starting point for a larger project where the applicability of iterative reconstruction in industrial inspection and metrology will be investigated further.

Keywords: Iterative reconstruction, high resolution CT, beam hardening, discrete reconstruction

1 Introduction

Although reconstruction is most commonly done with the algorithm of Feldkamp, David and Kress (FDK, [1]) there are alternative approaches, such as iterative reconstruction algorithms, which have shown promising results for the improvement of image quality. The main reason why these algorithms
are not used is because, in comparison with filtered backprojection, they result in longer reconstruction times. However, this can be compensated by using an efficient implementation on a graphical processing unit [2].

All iterative reconstruction methods start from an initial solution; usually this is an empty volume. This intermediate solution is forward projected to construct a calculated projection. The difference between this calculated and the measured projection is determined and backprojected using a weighted average. Subsequently this is added to the intermediate reconstructed volume; which is the update step of the algorithm.

There exist two main classes of iterative reconstruction methods: algebraic or statistical methods. The most important difference between these methods is that algebraic methods use integrated attenuation values in the update step, while statistical methods use the expected number of photons. In case of poor statistical information statistical methods can yield better results, but for scans with a sufficient photon flux and/or integration time, there is no added value for this more complex approach.

For the Simultaneous Algebraic Reconstruction Technique (SART), which is most often used at UGCT, the update process of a volume of $N$ cubic voxels is given by [3]:

$$
\mu_j^{(k+1)} = \mu_j^k + \lambda \frac{\sum_{r \in \phi} P_\phi \left( r_i - \sum_{n=1}^{N} W_{in} \mu_n^k \right) w_{ij}}{\sum_{r \in \phi} P_\phi w_{ij}}, \tag{1}
$$

where $\mu_j^k$ is the linear attenuation coefficient of voxel $j$ after the $k$-th iteration, $\lambda$ is a relaxation parameter, $r_i$ is the total measured attenuation along ray $i$ and $P_\phi$ is the projection with projection angle $\phi$. $w_{ij}$ represents the weights, which determine how much every grid point contributes to the total sum of the ray.

The aim of this article is to illustrate the current state in iterative reconstruction algorithms developed, implemented and used at UGCT and Inside Matters. Because of the challenges which are still met when applying iterative reconstruction in industry, a research project was initiated by several academic and industrial partners active in the Flemish Region, Belgium, to further investigate how these challenges can be tackled. The aim of the MetroCT project (supported by iMinds/ IWT) is to introduce more advanced iterative reconstruction methods such as model based iterative reconstruction, statistical reconstruction and discrete algebraic reconstruction, which have proven their added value in medical applications, in industrial CT.

2 Iterative reconstruction and limited number of projections

The FDK algorithm typically requires a complete dataset, including a large number of equiangular projections at a relatively long exposure time. It has been demonstrated that iterative reconstruction algorithms can provide improved results in case the projection data is limited to a certain angular range (limited angle tomography) or when the total number of available projections is limited and that they provide better noise handling [4].

Figure 1 shows a cross section of an FDK (Figure 1a) and a SART (Figure 1b) reconstruction of a polyurethane foam sample reconstructed with 2000 projections. It can already be observed that the noise handling is better in case of the SART reconstruction. However, the benefits of using iterative reconstruction algorithms enhance when reducing the number of projections $N_p$. Figures 1c and 1d
show the same slice of the same sample, reconstructed with the FDK and the SART algorithm respectively, but in this case only 50 projections were used. In the case of the FDK reconstruction it is difficult to distinguish the sample from the noise. Note that the better results for the SART algorithm are not exclusively based on the better noise handling of the SART algorithm, in [4] tests on a phantom without noise also resulted in better image quality for SART reconstructions with a reduced number of projections.

![Image](image1.png)

Figure 1: Cross section of a sample of polyurethane foam, reconstructed with FDK and 2000 projections (a), SART and 2000 projections (b), FDK and 50 projections (c) and SART and 50 projections. Although all algorithms operate in 3D, the result is shown in 2D for demonstration purposes.

### 3 Discrete iterative reconstruction

If the sample consists of one material (and air surrounding or inside the sample), then there are two possibilities for each voxel that does not belong to the border in the reconstruction. Either it belongs to the material of the sample and then it has a fixed value as attenuation coefficient: $\mu_1$, or it belongs to the air and its attenuation coefficient is zero: $\mu_0 = 0 \text{ cm}^{-1}$. So only two values (or a discrete number of values in case more materials are present) for the attenuation coefficient are possible instead of a whole range $\mu$'s. In discrete tomography [5] it is the purpose to obtain more accurate reconstructions by using the knowledge that the reconstruction should consist of only a few values. It is often used when only a limited number of projections are available. There exist several algorithms for discrete reconstruction, e.g. [6,7]. One of the algorithms is the Discrete Algebraic Reconstruction Technique for Experimental data (EDART) [8], which combines iterative with discrete reconstruction without significantly
increasing the reconstruction time in comparison with standard reconstruction. EDART includes a method to estimate the segmentation threshold and attenuation coefficient so no prior knowledge is required.

Although the SART reconstruction of the polyurethane foam with 50 projections was better than the FDK reconstruction, it is still difficult to segment the foam phase. Figure 2a shows the segmented cross section of the SART reconstruction of 2000 projections (for segmentation thresholding was applied using Otsu’s method [9] to automatically calculate the threshold). Figure 2b shows the segmented cross section of the SART reconstruction with 50 projections after applying a median filter and using Otsu’s method for thresholding and Figure 2c shows the EDART reconstruction (again $N_p$ =50). It is clear that the EDART reconstruction provides better results.

![Figure 2: Cross section of a sample of polyurethane foam, reconstructed with SART and 2000 projections and binarized using Otsu’s threshold (a), SART and 50 projections and binarized using Otsu’s threshold after applying a median filter (b) and EDART and 50 projections (c). Although all algorithms operate in 3D, the result is shown in 2D for demonstration purposes.](image)

### 4 Beam hardening

The X-ray spectrum for high resolution X-ray tomography is polychromatic, and X-rays with a low energy are more attenuated when propagating through a sample than X-rays with a high energy (hardening of the beam). The approximation of the X-ray interaction process as a simple
monochromatic Lambert-Beer determined process results in issues with beam hardening. These artefacts complicate the inspection of metallic parts produced with additive manufacturing and plastic components containing metal parts encountered in electronics, FMCG, and other industries.

It is possible to model this beam hardening and incorporate it in the forward projector of the SART algorithm, the update step in equation (1) then becomes [10]:

\[ \mu_j^{(k+1)} = \mu_j^k + \lambda \frac{\sum_{l \in P_\phi} \left( r_l - \sum_{n=1}^N w_{ln} \left( \frac{\mu_n^k}{1 + \alpha \sum_{i=1}^{n-1} \mu_i^k} \right) \right) w_{ij}}{\sum_{n=1}^N w_{in}} \cdot w_{ij}, \]

with \( \alpha \in [0, 1] \) per unit of \( \mu \) the strength of the correction per unit of \( \mu \) and \( \beta \in [2.5, 3.5] \) the energy dependency. The complete derivation of this equation can be found in [10]. Figure 3 illustrates the effect of this beam hardening correction (BHC) on a sample of a tooth implant. Figure 3a shows a cross section of this sample (reconstructed with SART \( N_p = 1200 \)) without BHC and Figure 4b shows the same cross section with BHC. It is clear that the cupping artefact is reduced.

Beam hardening complicates the use of discrete reconstruction algorithms as voxels belonging to the same material have no longer the same attenuation coefficient. However, it is possible to combine the EDART method mentioned above with BHC in equation (2) [11]. Figure 4c shows the cross section for a SART reconstruction with \( N_p = 20 \), figure 4d the EDART reconstruction with and figure 4e the EDART reconstruction with BHC. For BHC the paramaters \( \alpha = 0.0075 \) cm and \( \beta = 3.0 \) were used. The porous region inside the sample is better defined in Figure 4e than in Figure 4d, illustrating the importance of applying BHC.

Figure 3: Cross section of tooth implant sample, reconstructed with SART and 1200 projections without BHC (a), SART and 1200 projections with BHC (b) SART and 20 projections without BHC (c), EDART and 20 projections without BHC (d) and EDART and 20 projections with BHC (e). Although all algorithms operate in 3D, the result is shown in 2D for demonstration purposes. [11]
5 Conclusions

Iterative reconstructions algorithms are a useful alternative for reconstruction algorithms based on filtered backprojection for specific applications. These algorithms can be adapted so prior knowledge about the sample or the beam can be incorporated, which allows for the reduction of artifacts or the required number of projections. We have illustrated the advantages of these methods on industry relevant examples, although further research is required to allow the use of iterative reconstruction in a standard CT workflow.

Acknowledgements

The Special Research Fund of the Ghent University (BOF) is acknowledged for the doctoral grant to Loes Brabant.

References