

**Session 201 - Advance in reconstruction algorithms****(012) Computed tomography from limited data using a robust discrete algebraic reconstruction technique**\*X. ZHUGE<sup>1</sup>, K. J. BATENBURG<sup>1,2,3</sup>

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Obtaining accurate reconstruction from a small number of projection images is of high importance in many tomography applications. Many advanced reconstruction techniques has been proposed in the past for limited data problems. Most of them achieve such goal by exploiting the prior information we have on the object under imaging. For example, it has been shown that if the object has rather sparse boundaries, significantly improved reconstructions can be obtained by applying the total variation minimization technique (Beck and Teboulle, 2009). In another type of problem, the object under test consists of only a few different materials, each produces an approximately constant gray value in the reconstructed image. By incorporating this knowledge as prior information, discrete tomography (Batenburg, 2005) can produce superior reconstructions using significantly less data comparing to conventional reconstruction methods such as the filtered backprojection (FBP).

Discrete Algebraic Reconstruction Technique (DART) is one of such algorithm that utilizes the discrete nature of the object. Assuming the gray values are known, DART alternates iteratively between discretization steps of segmentation based on gray values, and continuous steps of reconstruction on the boundary of segmented image (Batenburg and Sijbers, 2011). DART has been successfully applied for reconstructing samples from applications in CT (Van Aarle, et al., 2014) and ET (Van Aert, Batenburg, et al., 2011). Despite its success in many cases, DART encounter problems when the projection data contain noise. The fact that DART imposes strict constrains on the boundary pixels during iterations leads to noises being spread over these boundary pixels. As a result, the reconstruction of the boundary regions becomes less accurate in the results from DART under noisy conditions.

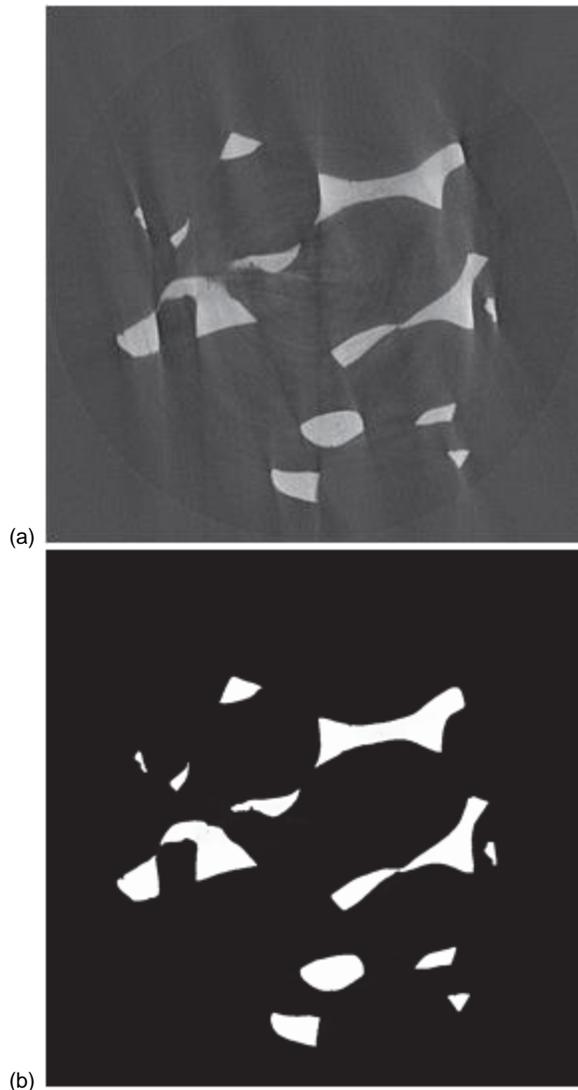
The main reason behind DART's problem of dealing with noisy projections is that the algorithm pushes abruptly the pixels toward discrete gray values in each iteration and fix the flat regions of the segmented image assuming these pixels are accurately reconstructed. This leads to spread of noise and errors in the boundary pixels. In this paper, we propose a robust discrete algebraic reconstruction technique (R-DART) which is performs more consistently against noise and mismatches than the original DART.

In the Robust DART, modifications are made on the procedure of algorithm. Firstly, the hard segmentation step is replaced with a soft segmentation function where the pixels are gently pushes toward the specified gray values. Second, the pixels that are greatly altered during the soft segmentation step are selected as free pixels, in contrast to the previous choice of boundary pixels. By smoothly steering the solution toward discrete gray values, the modified DART algorithm is less sensitive to noise and mismatches in the data than the original DART implementation.

Experimental  $\mu$ CT results show that the proposed algorithm yields accurate reconstructions under practical conditions. Figure 1 shows the reconstruction of a polyurethane foam taken with a SkyScan 1172  $\mu$ CT scanner. As we compare the results of a single slice of the full 3D reconstruction from FBP and the proposed algorithm, it is clear that our modified DART is able to maintain a high level of accuracy even using only 25 projections, in contrast to the significantly degraded results from FBP. Complete numerical and experimental studies will be included in the final paper.

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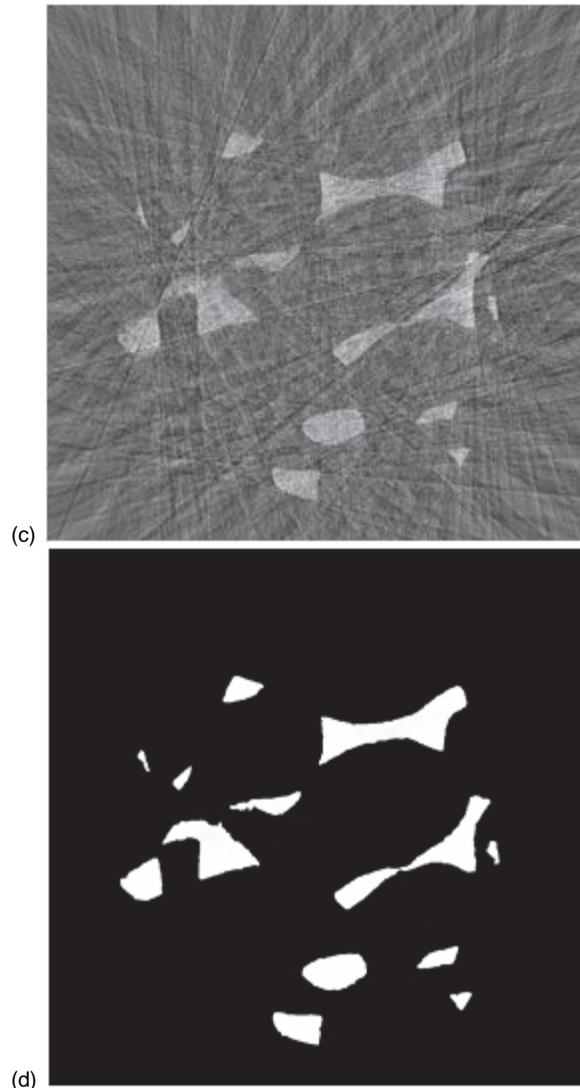


Figure 1: Comparison of reconstructions between FBP and the Robust DART using 500 and 25 projection images. (a) FBP using 500 projections, (b) Modified DART using 500 projections, (c) FBP using 25 projections, (d) Modified DART using 25 projections.

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