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Removal of curtaining effects by a variational model with directional forward differences

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ABSTRACT

Focused ion beam (FIB) tomography provides high resolution volumetric images on a micro scale. However, due to the physical acquisition process the resulting images are often corrupted by a so-called curtaining or waterfall effect. In this paper, a new convex variational model for removing such effects is proposed. More precisely, an infimal convolution model is applied to split the corrupted 3D image into the clean image and two types of corruptions, namely a striped part and a laminar one. In order to accomplish the decomposition we exploit the fact that the single parts have certain spatial structures, which are penalized by different first and second order differences. By doing so, our approach generalizes discrete unidirectional total variational (TV) approaches. A minimizer of the proposed model is computed by well-known primal dual techniques. Numerical examples show the very good performance of our new method for artificial as well as real-world data. Besides FIB tomography, we have also successfully applied our technique for the removal of pure stripes in Moderate Resolution Imaging Spectroradiometer (MODIS) data.

1. Introduction

The motivation for the present work was the analysis of aluminum matrix composites reinforced with silicon carbide particles by given high resolution 3D FIB tomography images.

FIB tomography, also known as serial sectioning, is an imaging technique, that has been used commercially for about 20 years. It is applied for preparation and direct observation of structural cross-sections and the generation of microstructural data in three dimensions. While classical *X*-ray tomography does often not reach the required material resolution, FIB tomography enables to investigate structures on a scale down to several nanometers.

The FIB system combines a classical scanning electron microscope with an ion beam. See Fig. 1 for an illustration. The ion beam mills and polishes the material sectionally, while the electron beam is used for imaging the surface after each section. Several hundred of these serial slices finally form a 3D image. For a more detailed introduction to FIB tomography we refer to Brandon and Kaplan (2008), Giannuzzi and Stevie (2005) and Munroe (2009). Unfortunately, such images often suffer from the so-called curtaining effect (Giannuzzi and Stevie, 1999; 2005; Zaefferer et al., 2008), see Fig. 2. This effect arises because the sputtering rates of the ion beam are sensitive to local changes in the surface structure. In particular below pores or cracks the rates vary and lead to stripe-like artifacts in the images. For the aluminum matrix composite in Fig. 2, e.g., at the phase boundary between aluminum and the reinforced silicon carbide particles, due to their locally varying material characteristics. Further, it may happen that the material is milled incompletely which leads to bright laminar artifacts. To reduce the curtaining effects a lower beam current could be used but this leads to a considerably higher milling time. Note that the whole imaging and milling process already takes about 25 h for each data set considered here. So further reducing the beam current leads to impractical processing times and therefore high expenses.

Instead, we propose a computational model to reduce curtaining effects. The corruptions in our data consist both of stripe-like structures due to different sputtering rates and laminar structures due to incomplete milling of the material. The corrupted parts cannot be used for the further analysis of the material unless the curtaining effects are removed. For our specimen in Fig. 2 this was the case for more than half of the data. The laminar corruptions are often cut off as they only occur in the lower part of the

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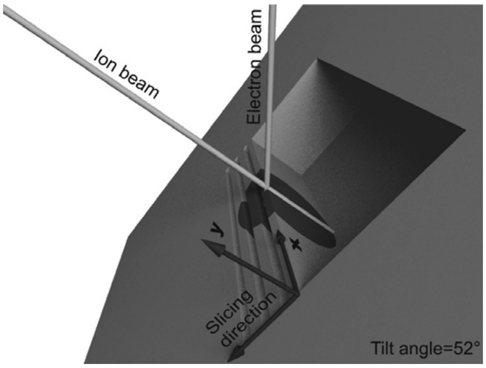

Fig. 1. Illustration of a FIB system. A focused ion beam mills slice by slice of the sample in z-direction and the exposed surface is imaged by an electron beam. Image credit: Velichko et al. (2008).

image. However, we will keep them since it is not desirable to throw away half of the data.

The problem of removing stripes in images was tackled by various approaches: Fourier based filtering was suggested in Chen et al. (2003) and Chen and Pellequer (2011), moment matching in Gadallah et al. (2000) and histogram based methods in Horn and Woodham (1979) and Rakwatin et al. (2007). Recently, variational models were successfully applied for the destriping of 2D images. The central idea in Bouali and Ladjal (2011) is the application of unidirectional discrete TV terms to extract the stripes by minimizing the functional

$$\arg\min_u \|\nabla_y(f-u)\|_1 + \lambda\|\nabla_x u\|_1, \quad \lambda > 0,$$

where f is the original image and u the destriped one. This method was improved in Chang et al. (2013) by adding a least squares data term and a framelet regularization term:

$$\arg\min_u \frac{1}{2}\|f-u\|_2^2 + \nu_1\|\nabla_y(f-u)\|_1 + \nu_2\|\nabla_x u\|_1 + \nu_3\|Wu\|_1, \tag{1}$$

where W denotes a Parseval framelet transform. It has been shown that this model gives much better results than the previous one even without framelet regularization, i.e., for $\nu_3 = 0$. The framelet regularization leads to another slight improvement. Finally, a more general method for the variational denoising of images with structured noise was developed in Fehrenbach et al. (2012), which has also been applied for destriping.

Applications of the aforementioned destriping methods are, e.g., the restoration of MODIS data (Bouali and Ladjal, 2011; Chang et al., 2013; Rakwatin et al., 2007) and FIB tomography images (Chang et al., 2013; Fehrenbach et al., 2012). In this paper, we focus mainly on the latter, where our FIB images are not only corrupted by stripe structured noise, but also by laminar effects. To the best of our knowledge the removal of curtaining effects involving additional large laminar parts was not considered before.

Compared to the above destriping methods our new model takes the following aspects into account:

A1) The existing destriping methods remove stripes only. Since our data is not only corrupted by stripes, we split the corrupted image not only into a clean part and stripes, but also into a third, laminar part.
A2) To avoid smoothing and to keep the small image details, we use a hard constraint for the decomposition of the corrupted image into the clean, the striped and the laminar part by applying an infimal convolution model.
A3) We consider 3D data whereas most destriping methods, except Fehrenbach et al. (2012), focus on 2D images.

To deal with A2) we propose an infimal convolution model for the splitting. The infimal convolution was applied for the first time in image processing by Chambolle and Lions (1997) followed by many other papers, see, e.g., the general discrete approach in Setzer et al. (2011) or the continuous function space approach in Holler and Kunisch (2014). We also refer to a nice PhD thesis on infimal convolutions Strömberg (1996). Infimal convolution models are in particular useful for the decomposition of images.

Various variational decomposition models were proposed in the literature. One example is the additive splitting into geometric and oscillating parts as texture and white Gaussian noise. For the first one typically TV- or Besov-seminorms are exploited. For the second one Meyers' G-norm (Aujol et al., 2003; Meyer, 2001; Strong et al., 2006), the norm of the dual Sobolev space H^{-1} (Osher et al., 2003; Vese and Osher, 2003), and the squared L_2-norm of the DCT-transformed texture (Starck et al., 2010) are well suited. For specifying the noise component also the norm of the dual Besov space $B^{\infty}_{-1,\infty}$ is used successfully in Aujol and Chambolle (2005). Decomposition models are as well applied for simultaneous structure-texture in painting, e.g., in Aujol et al. (2006) as an extension of the so-called morphological component analysis model (Starck et al., 2010). For the separation of point and curved structures based on wavelets (Besov norms) and shearlets or curvelets we refer to Kutyniok and Lim (2012) and Starck et al. (2010). *The clou of all these methods is the adaptation of the additive components to the task at hand.* For the curtaining problem we will show that our directional TV model is very well suited.

Organization of the paper. In Section 2, we introduce our variational model for the removal of curtaining effects and motivate its choice by the special structure of the corruptions. Then, in Section 3, a primal dual algorithm is presented for finding a minimizer that consists of the clean image and two types of corruptions. Section 4 demonstrates the performance of our algorithm for volume images obtained by FIB tomography as well as artificial

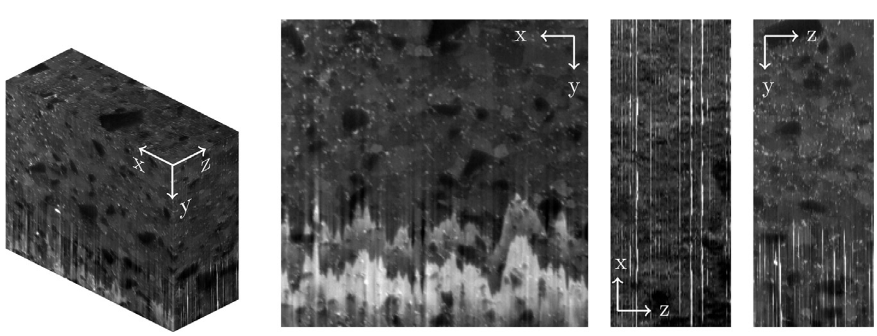

Fig. 2. Volume image of an aluminum matrix composite obtained by FIB tomography (255 × 255 × 100 pixels, i.e., 100 slices of size 11.6μm × 11.6μm) and typical slices in the $x-y$, $x-z$ and $y-z$ plane.

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