Parametric Reconstruction of Advanced Glass Fiber-reinforced Polymer Composites from X-ray Images

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Abstract
A novel approach to the reconstruction of glass fiber-reinforced polymers (GFRP) from X-ray micro-computed tomography (µCT) data is presented. The traditional fiber analysis workflow requires complete sample reconstruction, pre-processing and segmentation, followed by the analysis of fiber distribution, orientation, and other features of interest. Each step in the chain introduces errors that propagate through the pipeline and impair the accuracy of the estimation of those features. In the approach presented in this paper, we combine iterative reconstruction techniques and *a priori* knowledge about the sample, to reconstruct the volume and estimate the orientation of the fibers simultaneously. Fibers are modeled using rigid cylinders in space whose orientation and position is then iteratively refined. The output of the algorithm is a non voxel-based dataset of the fibers' parametric representation, allowing to directly assess fiber features and distribution characteristics and to simulate the resulting material properties.

Keywords: µCT, Materials Science, GFRP, Parametric Reconstruction, Tomography, Modeling of Microstructures

1 Introduction

Advanced composites such as GFRP integrate essential features for future materials such as low weight, function integration and cost-effectiveness, thus allowing for tailored components in many different industries. Composites typically consist of a matrix component, i.e. the resin matrix and the reinforcement component, i.e. the glass fibers, to achieve specific structural properties. X-ray micro-computed tomography (µCT) is an imaging method to study the internal structure of those composites in a non-destructive way and with high spatial resolution in the µm-scale. From a number of X-ray radiographs acquired from several angles, a volumetric image of the composites can be reconstructed. This image is then further processed to characterize features, such as the fiber orientation or pore size distribution [8]. The estimation of those features is useful for the estimation and optimization of the mechanical properties of the materials. During this process, some unwanted objects such as pores or inclusions of foreign particles could be introduced into the composite, which may influence those properties. Given the distribution and features of the fibers, those material properties can be simulated and analyzed. The most important features for this purpose are length and orientation, but one should also consider the inclusions and pores to give an accurate model of the material. Current methods to characterize structure properties of GFRP from high resolution µCT images rely on a sequential workflow, generally comprising the following steps. After reconstruction of the radiographs, the result is pre-processed to make the segmentation easier. The segmented image is then analyzed to, for example, quantify fiber lengths and/or pore size distributions [2-3, 6-7]. This conventional method suffers from poor precision and accuracy in the estimated parameters of the advanced composites, though. One of the reasons is using a grid of independent voxels for representing the material. While this is common in X-ray image reconstruction, it is unfavorable for fibers, which are typically very thin with a high aspect ratio relative to the voxel size. The resulting object voxels therefore exhibit substantial partial volume effects that hinder further quantification. Secondly, settings within the pipeline from reconstruction to individual object characterization are typically determined in empirical processes, relying mostly on the experience of researchers. That is, many parameters have to be set manually or semi-automatically, in several steps of the workflow, which may introduce additional errors. Finally, because the conventional workflow is unidirectional, any error that occurs in one of the steps will propagate through the whole pipeline. To correct for those errors, a feedback mechanism to correct for inaccurate estimates is needed.

2 Methods

In this work, we suggest a new GFRP reconstruction approach, in which fiber features are estimated during the iterative reconstruction of the image from the projection data. This is accomplished by integrating a parameter estimation step in the well-known Simultaneous Iterative Reconstruction Technique (SIRT) algorithm [1]. Our approach can be described as follows. After the µCT scan, an image is reconstructed by performing an iteration of SIRT, initialized by a completely black image. Each following iteration then starts with the three SIRT steps: 1) a forward projection of the current reconstruction, 2) calculation of the projection difference, called the residual sinogram, 3) update of the reconstruction using weighted back projection [5]. Here is where our approach hooks into the algorithm. We add a 4th step (e.g. every 10 iterations), where the parameters of the fibers in the sample are estimated. As the estimation procedure we plan to use the eigenvectors and eigenvalues of the Hessian matrix at scale σ = r, the radius of the fiber [4, 9]. In theory all current approaches to estimate a variety of measures can be employed at this step. The advantage of the approach being that the model will refine while the algorithm converges, alleviating the errors mentioned above. From the estimates obtained by the methods, a list of cylinders - representing each fiber in the sample - is created and used as a model to replace the fibers in the intermediate reconstruction image by rasterizing them with subvoxel accuracy. This added step provides the aforementioned feedback mechanism that refines the estimates of the fibers, as the reconstruction of the volume is refined.

3 Results and future research

To show how the algorithm works, we assume having acquired values for position, orientation and length of the fiber. We then simulate placing the fiber with an added, realistic inaccuracy in position that is closer to the correct position after each replacement step. This is supposed to mimic getting better and better estimates for the position oft he fiber. Before beginning the reconstruction, Gaussian noise with $\sigma_n = 1$ and $\mu_n = 0$ was added to the forward projection, to add further realism to the model. Figure 1 shows the same slice through the original phantom volume and the two reconstruction volumes side by side. Our phantom in this case is a single fiber of length 30 voxels and radius 2.5 voxels, oriented along the y-axis and positioned at the origin. It can clearly be seen that our approach gives a reconstruction that is much closer to the original phantom than a standard SIRT reconstruction. This is due to the fact that replacing the fibers does effectively eliminate the noise in the fiber voxels and enables SIRT to converge to a solution with higher contrast. In practice, replacing the fiber with correct gray values equivalent to the correct attenuation values will be a challenge.

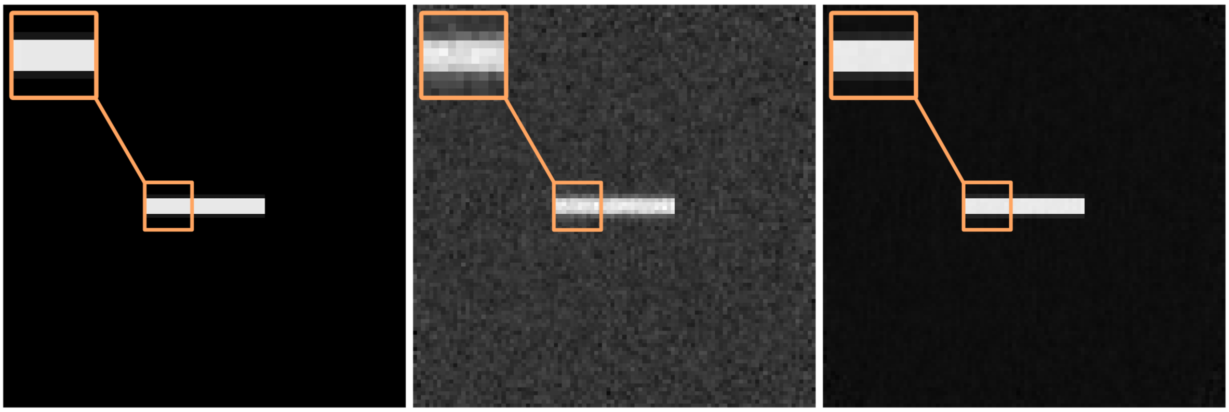

Figure 1: Synthetically generated phantom with a single fiber (left) and reconstructions of this phantom using standard SIRT (middle) and our approach with the added fiber replacement step (right). Gaussian noise with $\sigma_n = 1$ and $\mu_n = 0$ was added to the sinogram in both cases. Images have been normalized for increased visibility.

In the future we hope to improve the model to incorporate fiber orientation estimation as well as a model for inclusions, pores and resin matrix to get an accurate parametric representation of the GFRPs.

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