Machine Learning-based Single Fiber Extraction from Micro-CT Scans with GeoDict

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Abstract

Fibrous structures are present in many materials, including non-woven filter media used for filtration, carbon-fiber reinforced plastics or glass-fiber reinforced plastics used in mechanical applications, or gas-diffusion layers used in fuel cells. Spatial distribution, orientation, length, curvature and center line of fibers in materials like these are essential characteristics required in modern material design. Being able to analyze these properties from micro-CT scans is highly important to create precise models of existing materials. We propose a machine learning based algorithm to identify and extract the individual fibers in segmented 3D images to be able to fully characterize them.

Keywords: Single fiber extraction, machine learning, micro-CT, fibrous structures, GPU, neural network

1. Introduction

Nowadays, micro-CT scans are widely used for non-destructive testing. Although visual inspection is still used on micro-CT images, automatic and algorithmic analysis and characterization techniques are becoming increasingly relevant. Here, we focus on micro-CT images of fibrous structures which tend to have a highly complex shape that spans a large portion of the scanning domain. These fibrous structures and their fibers are present in many microstructures, including carbon-fiber or glass-fiber reinforced plastics used in mechanical applications, gas-diffusion layers used in fuel cells, or non-woven filter media used for filtration.

Most algorithms currently used to extract the statistics of the fiber orientations \cite{1, 2, 3} first split the image space into many small fiber segments and try to recombine the over-segmented fiber segments afterwards. These methods lack accuracy, because they often connect fiber center lines incorrectly. The center line determination is especially challenging in places where two or more fibers touch.

In the algorithm we introduce, artificial intelligence is used to guide the single fiber identification process. The three main issues we focus on is: generation of training data, training of the neural network, and use of the neural network on micro-CT data. With this method, we detect the boundary voxels between touching fibers, remove interface voxels, and separate the fibers for easy analysis.

![Figure 1: Structure model of a nonwoven material and the segmented fibers in fifteen different colors. In the right half, the single fibers have been assigned to one of fifteen different colors. Fibers that touch share the same color and correspond to connected components in the structure.](image-url)
2. Method overview

Many approaches to extract the statistics of the fibers from micro-CT scans focus on processing the skeleton of the fibrous structure and removing the crossings that form at fiber contact points. With increasing number of contacts, the complexity of the structures skeleton grows dramatically, limiting the success of this approach. We propose a machine learning based algorithm to identify and extract the individual fibers in segmented 3D images to be able to fully characterize the fibers and the overall composition of a material. Machine learning based on deep neural networks requires massive amounts of training data, in our case known fiber contacts. One approach could be to label these manually. However, this is not feasible for 3D data sets. Instead, we use GeoDict's [4] fiber structure modelling and scripting capabilities to generate training data sets, which consist of voxelized 3D fiber models and known fiber contact voxels.

2.1 Training the Neural Network

Supervised learning describes the process of training a deep neural network by showing it many different possible inputs and the correct outputs for these inputs. The inputs and results are called training datasets. In our case this means we need to be able to tell the network if a voxel is part of a bond point or not depending on the surrounding micro structure. In general, many thousands of training datasets are needed to successfully train a deep neural network. While possible for 2D image analysis, to prepare the training data manually can hardly be done for 3D micro-CT images. Using GeoDict, we are able generate thousands of microstructure models within a few hours. In these models the contact voxels are labeled automatically using the analytic information contained in the models. The challenge that remain is to create structure models in GeoDict with realistic fiber contacts that match the original micro-CT scans to allow the neural network to learn correctly.

2.2 Fibrous material modeling in GeoDict

In GeoDict, to generate fibrous material models, the fiber generator FiberGeo is provided with a set of parameters that represent the statistical properties of the material one wants to model. These parameters include fiber diameter, fiber orientation, porosity and others. Many different realizations (concrete geometries) of the same statistical model can be generated.

2.3 Generating Training Data

In the initial development of the fiber extraction method we focus on nonwoven materials without binder in them. In these types of materials, the centerline can have a very complex shape as the fibers are usually much longer than the scanning domain and bent randomly. This leads to very complex topologies. However, for these type of materials the quality of micro-CT scans is usually high and resolution of 5-6 voxels across the fiber diameter can be achieved without problems, while still obtaining a representative element volume. Also, the fibers in many nonwoven materials are round and of uniform diameter allowing us to limit the number of parameter we must vary in the model generation. For the training data generation, fiber diameter, porosity and maximum allowed fiber overlap were varied randomly. We allowed the fibers to be arbitrarily oriented (fully isotropic) to produce as many different configurations of fiber contacts as possible.
2.4 Extraction Method
After the neural network is trained it can be applied directly to a segmented micro-CT scan to identify the contact voxels between connected (undersegmented) fibers. These voxels are labeled differently from the remaining solid voxels in the micro-CT image. Afterwards, the labeled contact voxels (red voxels in Figure 2b) are removed from the segmented image to separate the fibers and therefore simplify the topology of the fibrous structure.
In the final step, the connected components are analyzed (Figure 2c) and a skeleton based approach is used to obtain the centerline of individual fibers. These centerlines are then traced to obtain an analytic geometric description of the material.

Figure 2: Fiber contact/bond detection and resolving.

3. Example
We applied our method to a nonwoven micro structure that has not been shown to the neural network before. The structure is generated from an analytic model containing 499 fibers. The neural network achieved a decomposition into 467 connected components. In this example all bond points were detected. The remaining error occurs not because contact points are not detected at all, but in some cases not all voxels of bond points were labeled correctly. These remaining connections between fibers results in the mismatch between number of fibers and connected components. For the future we want to improve the quality of the bond point detection to improve the separation and implement postprocessing steps to remove remaining connections.

Figure 3: Example of detected fiber bond points in a microCT image. The image shows fibers in white, background in black and the labeled bond points in red. The colors are attenuated with increasing depth simulating an SEM image.
For further experiments we identified the individual fibers an micro-CT scan of a glasfiber reinforced composite provided by Bruker MicroCT [5] and obtained 1641 connected components. This number includes fragments of fibers at the domain boundary that are currently not processed further. The result is visualized below.

![Figure 4: Glas fiber reinforced composite scan provided by Bruker MicroCT (left), individual fibers (right)](image)

### 4. Conclusion

The already existing algorithms to analyze fiber diameter, fiber orientations and fiber curvature already provided a lot of help to create virtual twins of fibrous materials. With the capability to extract individual fibers from micro-CT scans it is possible to analyze fibrous structures in a very detailed manner and create even more precise models with less manual work. For future developments we want to extend the capabilities of machine learning based fiber extract to work with even more and more types of fibrous materials and separate binder from fibers.

### References


