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TUComp framework for modeling and analysis of composite materials based on X-ray microtomography

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Abstract — Hereby presented is a TUComp suite of *Python* programs conceived to help in modeling and analysis of composite materials based on X-ray microtomographic scans. The approach combines existing libraries like *WEKA* learning algorithms library, *Google*'s *TensorFlow* for deep learning and *Blender* for 3D modeling with in-house developed algorithms based on implicit and dual kriging. The main applications of the system reach from the analysis of short fiber degeneration and identification of defects in manufacture with Resin Transfer Molding (RTM) to the automatic reconstruction of the realistic geometry of fibrous woven reinforcements to predict their permeability and behavior during compression.
Keywords — composites, Big Data, deep learning, X-ray micro-tomography.

1 Introduction

Composite materials constitute an ongoing challenge for designers and manufacturers alike, as their multiscale, inhomogeneous structure highly complicates the prediction of processing parameters required to achieve their theoretical potential of mechanical performance. This is true for all types of composite materials, both those reinforced with short fibers and with long fiber three-dimensional woven architectures

There exist some methods aiding in the identification of material structure and post-manufacturing defects, like X-ray microtomography for example. This method yields a detailed view of the internal structure of a composite specimen while retaining its integrity. The main drawback of this technique though is the sheer amount of data that requires treatment rendering any manual or simple analysis fairly useless from the quantitative point of view. To remedy this, we propose a deep learning TUComp [1] framework combining several *Open Source* tools with an in-house *Python* library that is dedicated to the automatic processing of X-ray microtomographic scans of composite materials. The main advantage of such approach is the minimization of user input and problem-oriented processing based on training data from previous analyses.

The rest of this paper is organized as follows : first, some of the challenges present during analysis of X-ray microtomographic scans are presented on the example of fiber morphology analysis, followed by phase segmentation and description of the extraction of weave geometry. The summary of the TUComp framework concludes the article.

2 Analysis of morphology

Analysis of defects constitutes one of the main applications of the X-ray microtomography in materials. Most of the manual analyses are very limited when performed on 3D reconstructions due to the complexity of the material, as can be observed in the case of short hemp fibers in a polymer matrix (Fig. 1). Despite the low, less than 5% fiber volume fraction, more than 1.7 million objects require analysis. Transformation of volumetric data into surface meshes followed by the extraction of geometric features allows for a much more informative depiction of fiber morphologies present (Fig. 2). The arrangement of individual fibers by volume (Fig. 2a) or length (Fig. 2b) not only shows the shape of the probability

1. TUComp : *Tidying Up Composites*

distribution but also the difference of three orders of magnitude in feature value between phase elements and the morphology of fibers falling into each histogram bin. The geometric features can be further used for an automatic identification of new fiber morphologies (Fig. 3), otherwise unnoticeable by a human operator.

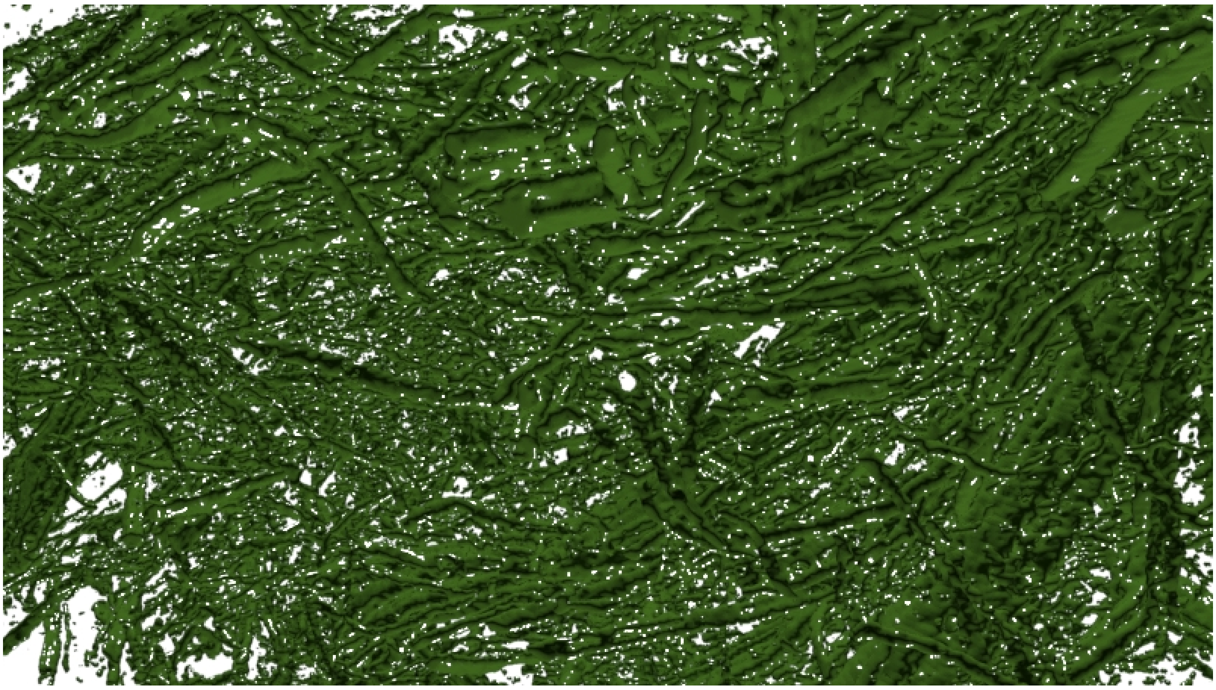
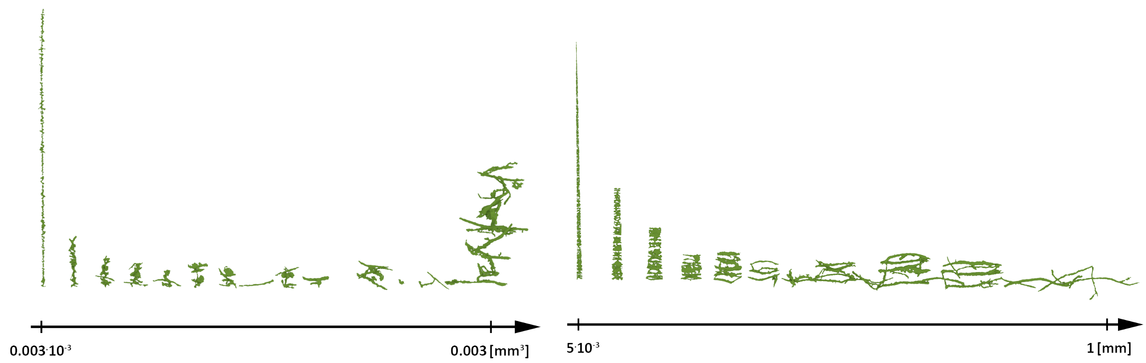


FIGURE 1 – Geometry of 1.7 millions of short hemp fibers reconstructed from an X-ray microtomographic scan.



(a) fiber volume

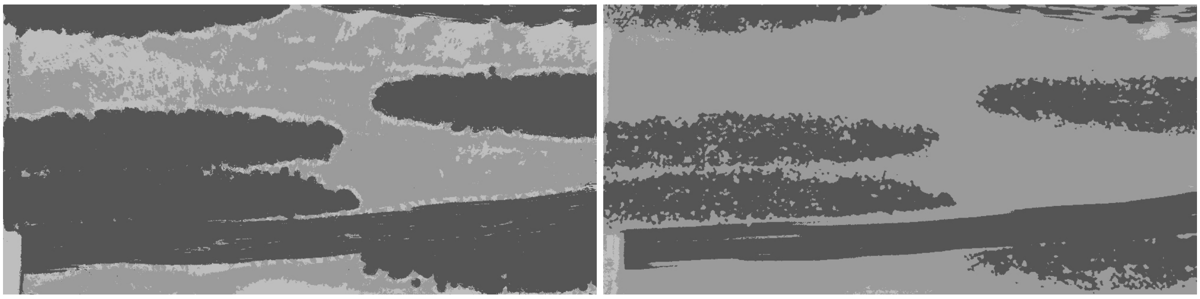
(b) fiber length

FIGURE 2 – Short hemp fibers arranged by their (a) volume and (b) length.

FIGURE 3 – Different short fiber morphologies identified with clustering.

3 Phase segmentation

The segmentation step provides binarized 2D images of each phase element which can be then transformed into 3D surface or volume meshes. The module can be used in a manual or automatic mode. The manual approach requires user input to create a training set for phase identification with learning algorithms. The automatic mode will use the existing database to identify different phases in the material and automatically create suitable training sets. The latter approach is usually more efficient because it builds the training sets based on several scans contrary to the manual selection that may be limited to a single 2D image chosen arbitrarily. The examples of images segmented with different methods are shown in Fig 5. The manual segmentation presents better results for new, previously unencountered materials, but it will still benefit from further automatic refinement.



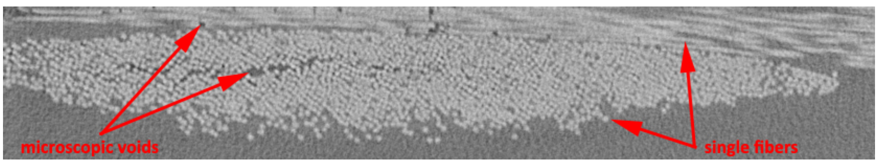
(a) manual segmentation mode (b) automatic segmentation mode

FIGURE 4 – X-ray tomographic scans segmented using (a) manual and (b) automatic mode.
White : voids, gray : polymer, black : fibers.

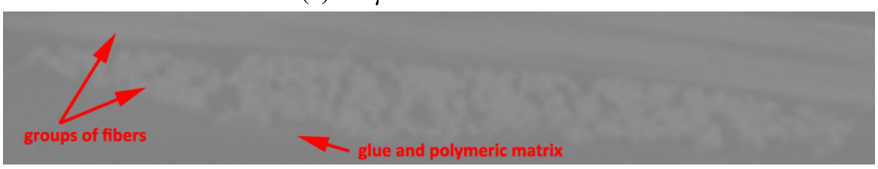
4 Weave geometry

The segmented data will have different characteristics depending on the scan properties, especially the resolution. Whereas a scan at 1.7 μm will show the contours of individual fibers (Fig. 5a), the 9.3 μm scan will show a much larger part of the specimen, but only the external contours of a fiber tow will be visible. Each case will require a different approach for extraction of weave geometry.

To identify the weave architecture, the high-resolution scans are first reduced in size automatically to speed up the processing and match the requirements of tow identification system based on *Haar*-like features trained with *Inception v3*. The identified fiber tow cross-sections can be further used for detection of weaving pattern as shown in Fig. 6. After identification, the surface geometry of each fiber tow can be reconstructed with dual kriging with a level of detail requested by the user. If the high-resolution scans are available, a detailed analysis of microscale porosity can be performed, useful for permeability predictions. A detailed description of the weave geometry reconstruction process is provided in [6] for high and in [5] for low-resolution scans.



(a) 1.7 μm scan resolution



(b) 9.3 μm scan resolution

FIGURE 5 – X-ray tomographic scans with (a) 1.7 μm and (b) 9.3 μm resolution.

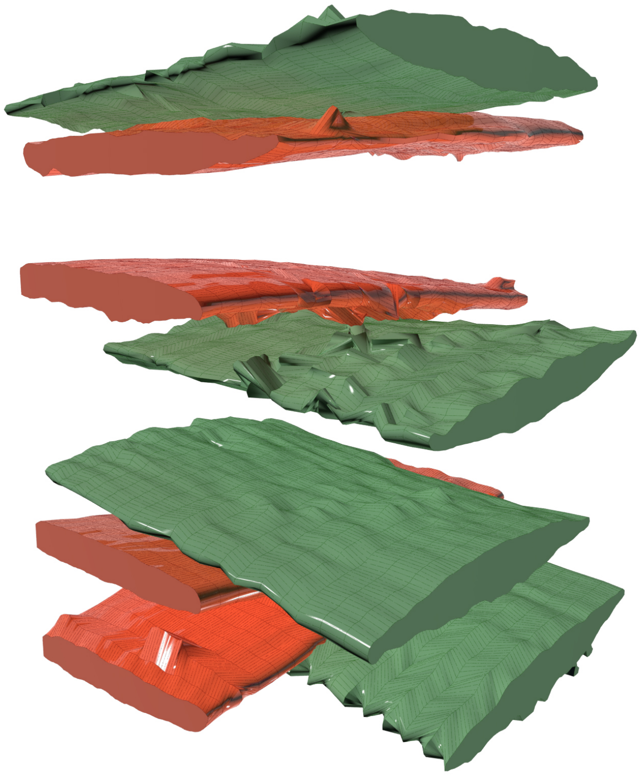


FIGURE 6 – Weave pattern extracted automatically from the X-ray microtomographic scan.

5 TUComp framework

The TUComp is composed of a *Python* backbone with links to various *Open Source* libraries that were deemed more efficient for performing specific tasks, like for example drawing NURBS surfaces of composite models in *Blender* [1]. The outline of TUComp components is presented in Fig. 7.

First module, *Segmentation* is dedicated to processing the raw scan data from X-ray microtomography. It calls *OpenCV* [4] *Python* library for fast image processing and *WEKA* from University of Waikato [3] for learning algorithms-assisted identification of different phases in the material.

The segmentation data can be either fed to the *Phase Analysis* module which provides quantitative data on phase percentage and spatial distribution or it can also be further used for modeling the phase geometry. In the case of short fibers, the surface geometry of each fiber can be modeled in *Blender* with NURBS surfaces and used for extraction of geometric features like volume, length and orientation, useful in the analysis of the manufacturing process. For woven fibers, the segmentation data is sent to the *Kriging* module to reconstruct the architecture of the weave. The identification of individual fiber tows is realized with *Haar Cascades* [8] trained with *Inception v3* module of *TensorFlow* deep learning library provided by *Google* [7]. Then the fiber tow geometry is further reconstructed with an implicit form of dual kriging described in [5]. The individual tows can be further sent to *Phase Analysis* module for statistical analysis of properties.

The final module, *Generation*, gathers all data from the *Phase Analysis* and *Kriging* modules and instructs a *Python* program to build a new composite with similar properties bounded by a user-defined domain. The results of such reconstruction can be viewed again with the *Phase Analysis* module or as surface meshes in *Blender*.

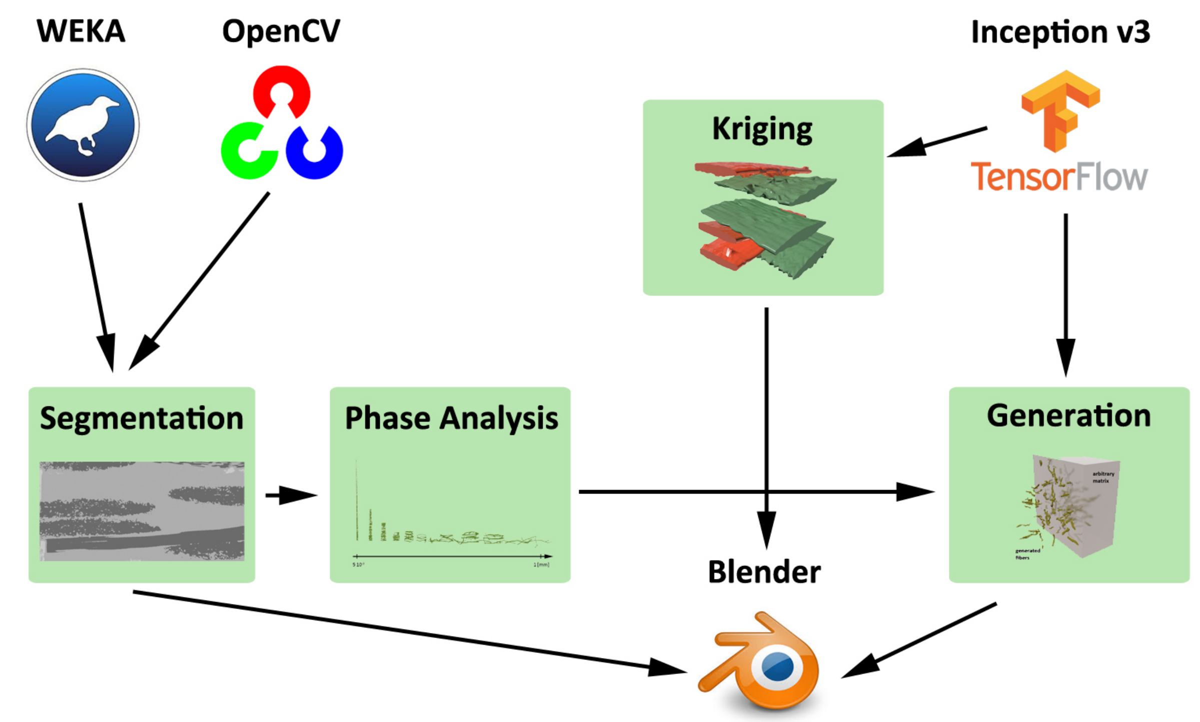


FIGURE 7 – A global view of components and external libraries that constitute the TUComp framework.

6 Conclusions

The presented framework is capable of performing an automated treatment of *Big Data* datasets from X-ray microtomography of composite materials. The treatment is tailored to specific requirements such as phase analysis, geometry reconstruction or morphology identification, and through the application of deep learning strategies, it can be applied to new cases of materials with no significant intervention is required from the user. The future developments will include semantics for the post-manufacture defects and further integration of processing errors into the creation of stochastically adjusted material models.

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