C. R. Mecanique 346 (2018) 532–538

Contents lists available at ScienceDirect

Comptes Rendus Mecanique

www.sciencedirect.com

Model reduction, data-based and advanced discretization in computational mechanics

# Diffuse manifold learning of the geometry of woven reinforcements in composites

Anna Madra [a,*], Piotr Breitkopf [b], Balaji Raghavan [c], François Trochu [d]

[a] *Department of Aeronautics and Astronautics, Massachusetts Institute of Technology, Cambridge, MA 02139, USA*
[b] *Laboratoire Roberval, UMR 7337, UTC–CNRS, Université de technologie de Compiègne, Centre de recherches de Royallieu, CS 60319, 60203 Compiègne cedex, France*
[c] *Laboratoire de génie civil et génie mécanique, EA 3913, INSA Rennes, 35708 Rennes, France*
[d] *Chair on Composites of High Performance (CCHP), Mechanical Engineering Department, Center of Research on Polymers and Composites (CREPEC), École polytechnique de Montréal, Montréal H3C 3A7, Canada*

ARTICLE INFO

*Article history:*
Received 16 November 2017
Accepted 21 March 2018
Available online 27 April 2018

*Keywords:*
Model reduction
Diffuse Approximation
Composites
X-ray microtomography

ABSTRACT

When attempting to build mesoscale geometric models of woven reinforcements in composites based on X-ray microtomography data, we frequently run into ambiguous situations due to noise, particularly in contact zones between fiber tows, resulting in inadmissible cross-sectional shapes. We propose here a custom-built shape-manifold approach based on kernel PCA, *k*-means classification and Diffuse Approximation to identify, "repair" such badly segmented shapes in the feature space, and finally recover admissible shapes in the original space.


## 1. Introduction

In the field of aeronautics, and increasingly in the automobile sector, composites with woven reinforcements are the material of choice for high-performance applications. 3D volume imaging techniques such as X-ray microtomography provide detailed information on the geometry of the material at the micro- and mesoscales. Geometrical reconstruction based on microtomographic scans gives us an opportunity to create realistic numerical models suitable for finite element simulation of the manufacturing processes involved or for identifying the mechanical properties of the material by homogenization.

However, several challenges emerge while creating such geometric reconstructions. Firstly, the microtomographic scans need to be segmented, i.e. the elements corresponding to particular fiber tows composing the woven architecture must be identified, e.g., by determining the contours of the tow cross-sections on consecutive 2D slices of the scan. This process may be performed manually [1], by analyzing directional gradients [2] or using learning algorithms [3]. The manual approach is clearly impractical, since a single scan is composed of thousands of slices that would each require individual treatment. On the other hand, automated segmentation may yield a possibly oversimplified geometry as in the case of gradients, or mostly well-segmented, detailed contours with a certain percentage of outliers, as is the case of the learning algorithm approach [4].

In this paper, we propose tackling the issue of outlier fiber tow contours that are incorrectly segmented by using a learning strategy [3]. We begin by projecting the level-set contour snapshots of individual contours onto the feature space

* Corresponding author.
*E-mail address:* amadra@mit.edu (A. Madra).

https://doi.org/10.1016/j.crme.2018.04.008

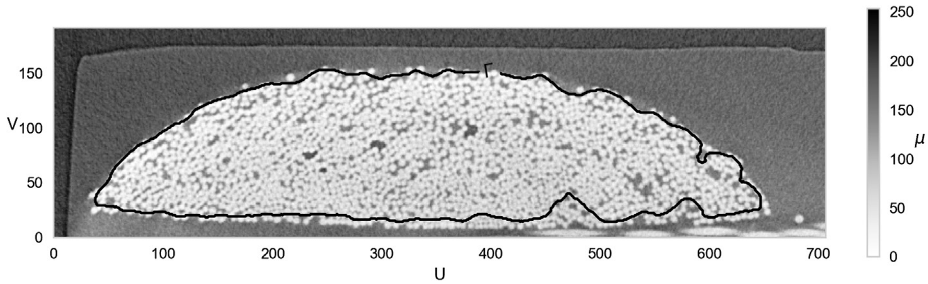


**Fig. 1.** 2D slice of an X-ray microtomogram with indicated contour Γ of the segmented fiber tow, grayscale values correspond to the value of X-ray attenuation coefficient $\mu$; a plausible fiber tow contour is indicated by the black line.

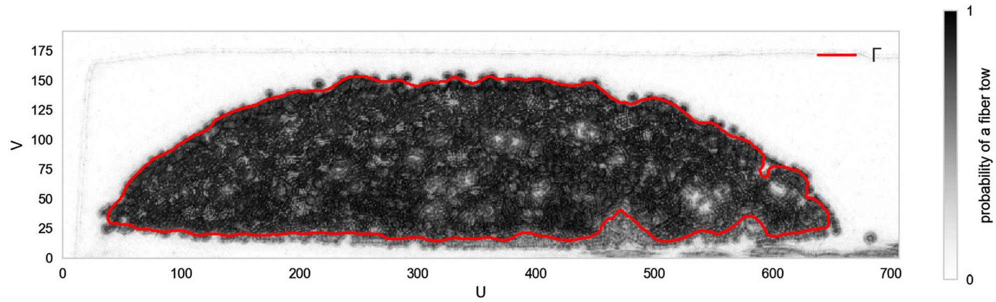


**Fig. 2.** Segmentation result, grayscale values correspond to the probability of tow detection. Properly identified, *regular* fiber tow section in red.

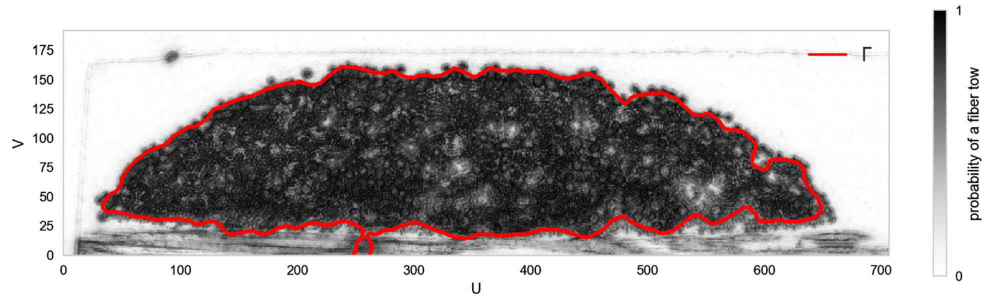


**Fig. 3.** Incorrectly detected, *outlier* fiber tow contour (red line); note the segmentation error zone at $U = 260$, $V = 0$.

using kernel-PCA [5], followed by classification using a $k$-means algorithm. The clusters of outliers are then identified based on an *ad hoc* criterion (e.g., failure to preserve the volume of individual fibers) and are then removed from the snapshot base which is *once again* decomposed using kernel-PCA. The shape manifold(s) of the admissible contours is/are then described by using Diffuse Approximation in the feature space. A "repaired" outlier is then hypothesized as the closest point on the manifold of admissible shapes and is obtained in the form of a set of diffuse weights with respect to neighboring admissible shapes. Finally, these weights allow us to solve the pre-image problem, i.e. finding the actual shape of the "repaired" fiber tow section in the *original* observation space.

## 2. Contour representation in feature space

Consider a series of contours $\Gamma^{(i)}$, $i = 1, \ldots, N_t$ of a fiber tow cross-section obtained by structure segmentation using learning algorithms of $N_t$ subsequent 2D slices of a tomogram. A sample contour is shown in Fig. 1.

The number of individual fibers in a fiber tow is considered constant and post-processing of the image gives us the first information as to whether a given section may be considered as a *regular* one (Fig. 2), exhibiting an admissible variability due to the measurement error (which can be further taken into account for example, by introducing the "nugget effect" in kriging approximation [3]) or it must be classified as an *outlier* (Fig. 3) requiring special treatment like the one presented in the present work.

Each contour, regular or outlier, simply or multiply connected, may be represented as the zero level set of a level set function $\phi$ [6] defined within the whole image slice such that