



Computation of permeability of a non-crimp carbon textile reinforcement based on X-ray computed tomography images



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ABSTRACT

The paper demonstrates the possibility of a correct (within the experimental scatter) calculation of a textile reinforcement permeability based on X-ray micro-computed tomography registration of the textile internal architecture, introduces the image segmentation procedures to achieve the necessary precision of reconstruction of the geometry and studies variability of the geometry and local permeability. The homogenized permeability of a non-crimp textile reinforcement is computed using computational fluid dynamics with voxel geometrical models. The models are constructed from X-ray computed tomography images using a statistical image segmentation method based on a Gaussian mixture model. The computed permeability shows a significant variability across different unit cells, in the range of $(0.5 \dots 3.5) \times 10^{-4} \text{ mm}^2$, which is strongly correlated with the solid volume fraction in the unit cell.

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1. Introduction

Fabrication of fibre reinforced composites by (liquid) composite moulding involves impregnation of the dry reinforcement with a low viscosity resin, which is injected into the mould cavity [1]. In the process of impregnation, the liquid resin flows through the system of channels inside the reinforcement, which can be considered as a porous medium. The flow of a liquid through a porous medium is described by the Darcy's law, which states a dependence of the flow velocity on the permeability of the medium, viscosity of the liquid and the applied pressure gradient. The permeability of the composite reinforcement is determined by the size and shape of the flow channels inside it; it is usually anisotropic and can be described by a second order tensor. Permeability is an important parameter of the technological process, which determines the quality of the impregnation and the duration of the production cycle. For the simplest and ideal case of unidirectional arrangement of fibres, analytical models have been developed, which allow to calculate the longitudinal and transversal permeability as a function of the fibre radius and volume fraction [2,3]. The structure of textile fabrics is more complex and includes two levels – the channel network between the yarns, and the intra-yarn

channels, where the liquid can flow in the space between fibres [4]. The intra-yarn structure can be considered as a unidirectional arrangement of fibres; its permeability can be estimated from analytical models with fair accuracy. The level of yarns, however, is more complex; its contribution to the permeability of the preform is determined by the parameters of the preform: weave type, fibre volume fraction, yarn linear density, sett and crimp [5,6]. Calculation of the permeability of composite preforms can be done by numerical methods, through the flow simulations, but it requires a detailed description of the geometry of the flow channels.

A number of architecture-specific approaches to the estimation of permeability of composite preforms were developed, which use idealized models of the flow channels in the preform [7–12]. Calculation of the permeability on the basis of a constructed model can be done through the solution of the Navier–Stokes or Stokes equations with finite element [13] or finite difference [14] discretization. More realistic models can take into account perturbations of the geometry or the features introduced in manufacturing of the fabric [15–18]. Stochastic models of the reinforcement, calibrated using X-ray computed tomography (μ CT) data, allow generating virtual instances of the material [19–21]. Application of μ CT to the permeability determination involves processing of three-dimensional images of composite samples to extract geometrical characteristics of the preform and use these data to construct a model directly or to combine them with an ideal model. As the

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Table 1
Dimensions of the samples, image resolution and number of unit cells.

	Dimensions (mm)	Resolution of micro-CT image (μm)	Number of unit cells
Sample #1	$2.45 \times 3.78 \times 4.00$	2.25	1×2
Sample #2	$9.79 \times 8.32 \times 4.00$	6.00	4×4
Sample #3	$6.32 \times 5.93 \times 4.00$	4.20	3×3

permeability of a preform depends on the geometry and the volumetric fraction of flow channels, the most important step in the modelling is the image segmentation, which extracts the phase boundaries. Usually this is done using grey-value thresholding [22,23], however this method requires re-calibration of the algorithm with experimental data for each image due to the fact the threshold is specific for the image acquisition parameters and the type of material. Up to now the image segmentation methods were not precise enough to allow calculation of the textile permeability (which is extremely sensitive to the details of geometrical reconstruction) with the precision with experimental scatter. At least (to the best knowledge of the authors) there is no published demonstration of such calculation. In the present paper we demonstrate that this goal can be achieved.

This paper presents the results on the determination of the permeability of a non-crimp carbon textile reinforcement based on μCT images. The computation of the permeability is done using simulations of the fluid dynamics with voxel models, constructed from the μCT images of the material samples. The voxel models are constructed using a statistical algorithm for image segmentation, based on the Gaussian mixture model, which belongs to the class of supervised classification. This method does not require calibration with experimental data due to the fact that it is based on the quantities, extracted from a μCT image, which reflect local physical properties of the material. The results are validated with experimental data. The validated calculation of permeability allows studying its variability for different unit cells of the textile, extracted from an image of the same sample.

The paper is structured as follows. Section 2 describes the material, the samples and the μCT used in the study. Section 3 describes the segmentation algorithm. Section 4 explains the computation procedure for the permeability. Section 5 presents the results, including comparison with experiment and variability study, and Section 6 contains the discussion and conclusions.

2. Material, samples and micro-CT imaging

The material used in the study is a non-crimp carbon/epoxy composite from Saertex (540 g/m^2 , +45/–45, franse stitch). The manufactured test plate had a thickness of 4.0 mm and a resulting fibre volume fraction of 45.5%. The plate was produced from six layers of the dry fabric impregnated by the resin RIM 135 and the hardener RIMH 136.6 from Momentive, and cured at a temperature of 25 °C. The data on the permeability of the studied NCF reinforcement is presented in [24]: at a fibre volume fraction of 50.8% the saturated permeability was measured as $0.5 \times 10^{-4} \text{ mm}^2$ (in the 45° direction to the production direction). Based on linear fit of the fibre volume fraction – log (permeability) dependencies presented in [25] for non-crimp fabrics, similar to the one studied here, the permeability at fibre volume fraction of 45.5% can be estimated as $(1..2) \times 10^{-4} \text{ mm}^2$. Three samples of different size were cut from the plate and scanned with the Nanotom X-ray computed tomography system (General Electrics). The dimensions of the samples, the resolution of the image and the number of unit cells (representative volume elements) in each sample are given in Table 1. The size of the unit cell was obtained

by measuring bundle insertion density with ImageJ. Cross-sections of the micro-CT images are shown in Fig. 1.

3. Image segmentation algorithm

In the context of the present study, segmentation is a problem of finding in the image a set of non-overlapping domains, corresponding to the components of the voxel¹ model, which are solid and fluid phases. The task of segmentation therefore involves classification of each voxel of the model into a finite set of classes. This classification was done using two feature variables: average grey value and structural anisotropy. Denoting the grey value distribution in the image as $I(\mathbf{p})$, the average grey value is calculated as:

$$g(\mathbf{p}) = \int_W I(\mathbf{p} + \mathbf{r}) d\mathbf{r}$$

where W is the integration window, and $d\mathbf{r} = dx_1 dx_2 dx_3$. Structural anisotropy is defined as follows:

$$\beta(\mathbf{p}) = 1 - \frac{\lambda_1}{\lambda_3}$$

where $\lambda_1 \leq \lambda_2 \leq \lambda_3$ are the eigenvalues of structure tensor:

$$S_{ij}(\mathbf{p}) = \int_W \frac{\partial I(\mathbf{p} + \mathbf{r})}{\partial x_i} \frac{\partial I(\mathbf{p} + \mathbf{r})}{\partial x_j} d\mathbf{r}$$

Here vector \mathbf{p} defines the position of the centre of the integration window in the global coordinate system of the image. Vector \mathbf{r} is the relative position of a pixel of the image inside the integration window (Fig 2).

The segmentation was performed by constructing a statistical model for the g and β distributions in the form of a mixture of bivariate Gaussian distributions. In order to construct the model, small regions of interest (ROI) were selected in the image, which contained a single component of the material. The feature variables g and β were calculated inside the selected ROI on a regular grid, with the density of the grid chosen so that the total number of points was sufficiently large (>1000). Fig. 3 shows the ROIs, selected in sample #1 and the distribution of the obtained data points in $\{g, \beta\}$ feature space. The obtained points in i -th ROI were fitted with a bivariate Gaussian distribution $N_i(\boldsymbol{\mu}_i, \boldsymbol{\Sigma}_i)$, where $\boldsymbol{\mu}$ and $\boldsymbol{\Sigma}$ are the mean vector and the covariance matrix of the distribution. Parameters of the distributions were calculated using maximum-likelihood estimation:

$$\boldsymbol{\mu} = \frac{1}{N} \sum \mathbf{X}$$

$$\boldsymbol{\Sigma} = \frac{1}{N-1} \sum (\mathbf{X} - \boldsymbol{\mu})(\mathbf{X} - \boldsymbol{\mu})^T$$

where $\mathbf{X} = [g, \beta]^T$. Note that the mean $\boldsymbol{\mu}$ is defined on the basis of the variable g , which is obtained as an average over integration window, whereas the $\boldsymbol{\mu}$ itself is an average over a selected ROI. In general, orthogonal yarn systems in micro-CT images have slightly different distributions of feature variables (evidence for this was

¹ The term “voxel” in this context refers to an element of a model rather than to a pixel of a 3D image.

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