3D Fiber Orientation Characterization of Nonwoven Fabrics using X-ray Micro-computed Tomography

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Abstract: Three-dimensional (3D) fiber orientation in nonwoven fabrics is highly relevant to an extensive spectrum of end-uses including, but not limited to, thermal insulations, paper products, composite fabrication, compact heat exchangers, fibrous filters and membranes. In spite of extensive research conducted on 2D determination of fiber orientation in nonwoven fabrics, 3D determination of fiber orientation in nonwovens is still in its infancy. In this study, direct observation of 3D fiber orientation was achieved by the use of X-ray micro-computed tomography (µCT). The employed approach allows the calculation of orientation tensor to be made for each fiber. The approach is comprised of four major steps including, smoothing, segmentation, skeletonization and fiber tracing which provide the extraction of the position and length of individual fiber. Prior to application of proposed algorithm to realistic 3D images of nonwoven fabrics, the performance of the algorithm was evaluated by its application to 3D virtual structures simulated with predefined spatial orientation. It was established that the proposed method is an efficient tool in 3D determination of fiber orientation in nonwoven fabrics.

Keywords: Nonwoven fabric, 3D fiber orientation, Orientation tensor, Skeletonization, X-ray micro-computed tomography.

1. INTRODUCTION

Nonwoven fabrics are usually manufactured directly from fibers, thus partially or completely eliminating conventional textile operations, such as drawing, roving, spinning, weaving, or knitting. The simplicity of fabric formation, coupled with high productivity and low specific gravity, allows nonwovens to compete favorably with woven or knitted fabrics in terms of performance and cost in applications ranging from simple low cost replacements for more costly conventional textiles to high-performance specialty textiles [1,2].

Fiber orientation is an important parameter affecting the geometrical, mechanical, and hydraulic properties of nonwoven fabrics. Determination of fiber orientation distribution in nonwoven fabrics is highly relevant to an extensive spectrum of end-uses inclusive of paper production [3,4], filtration [5,6], compact heat exchangers [7,8], fibrous beds for manufacturing processes [9,10], fuel cell technology [11,12], and transport in biological systems [13,14]. In depth perception of the 3D fiber orientation distribution is the prerequisite for modeling and engineering of nonwovens, which has become a challenge to nonwovens fabric design engineers.

Direct tracking [15], Fourier transform [16,17], flow field analysis [18], Hough transform [19,20], and principal component analysis [21,22] form the commonly practiced techniques in quantification of 2D fiber orientation in nonwovens. These techniques provide trivial details on the architecture and inner structure of nonwoven fabrics. Despite extensive research on 2D fiber orientation in nonwoven fabrics, 3D fiber orientation determination in these materials is still in its infancy [23], which calls for the need for development of techniques for 3D determination of nonwovens fiber orientation.

Rawal et al. [24] determined the fiber orientation distribution using 2D image analysis of fabric cross-section. The fibrous media was embedded in a polymeric resin and sectioned in two planes (x – z and y – z, where x correspond to the machine direction in the fabric. Shim et al. [25] used digital volumetric imaging (DVI) which is based on serial sectioning and imaging of samples. Initially fibers were dyed by fluorescent dye stuff, which was followed by dehydration, and embedding in polymeric resin. The 2D cross-sections were then combined and volume-rendered to construct a 3D image of the microstructure. Despite of availability of 3D images, 2D analysis of fiber orientation distribution of fabric cross-sections in x – z, y – z and x – y planes was carried out. Inevitable alteration of microstructure during sample preparation is the major drawback associated with this technique [25,26].

X-ray micro-computed tomography imaging or µCT is a fresh opportunity, which opens up new horizon in
understanding of the intricate 3D structure of nonwovens. In recent years, this technique has been successfully employed in measuring 3D fiber orientation in fiber reinforced composites [27-29]; however, the studies on nonwoven fabrics are very scarce [30,31].

The above review is by no means exhaustive; however it highlights the crucial effect of fiber orientation on physical and mechanical properties of nonwoven fabrics. The literature of the subject seems to favor research 2D orientation in nonwoven fabrics with less data available on 3D analysis of fiber orientation. In a recent study [30], the authors demonstrated the successful application of μCT in the generation of the realistic 3D model of nonwoven fabrics. The present study is an extension of the application of μCT in determination of 3D fiber orientation of nonwovens. Section 2 outlines an introduction to X-ray micro computed tomography. In Section 3 experimental methods used to produce and characterize nonwoven fabrics are reported. Section 4 presents a discussion of the results. This is followed by conclusions in Section 5.

2. X-RAY MICRO COMPUTED TOMOGRAPHY PRINCIPLE

μCT is a noninvasive and nondestructive imaging technique where individual X-ray images recorded from different directions are used in reconstruction of the internal structure of the object at high spatial resolution [32]. High resolution μCT has gained considerable importance and there exists published literatures that demonstrate the versatility of μCT in fields such as, geosciences [33,34], material science [35], and biology [36].

Figure 1 depicts the schematic illustration of μCT imaging technique. The specimen is placed on a rotary stage between the X-ray source and the detector. The specimen is irradiated with X-rays as it rotates through 180°. Upon traversing through the specimen, the emerged attenuated radiation is captured by the detector array. The attenuation is correlated with the specimen density and is typically represented as a grey scale conforming to a 2D pixel map. A projection radiograph is taken per each degree of rotation. The projections are reconstructed by a computer cluster equipped with filtered back projection algorithm to a volume data set. Each voxel represent a particular region of the sample where the grey value reflects density properties of the region. Image processing is used for visualization of μCT data and extraction of information from the image [32,37].

3. EXPERIMENTAL

3.1. Nonwoven Production

This study investigates nonwoven fabrics prepared using 11 dtex 90 mm long staple polypropylene fibers supplied by Mahoot Co. Fibers were processed on a 2.5-meter-wide double swift carding machine equipped with volumetric hopper feeder together with a commercial horizontal cross-lapper. Initial stabilization of the fibrous webs, was carried out on a taker needle loom. In order to increase uniformity, the stabilized pre-needled layers were superimposed on each other using a laboratory needle loom running at strokes frequency of 330 strokes/min. This additional needling operation yielded to production of needled nonwoven fabric weighing 370 g/m². A total needling density of 50 needle/cm² and needle penetration depth of 12mm using Groz-Beckert felting needles was used during final needling stage.

3.2. Image Acquisition

Image data for nonwovens was acquired using the Phoenix Nanotom X-ray tomography machine, housed in the School of Chemical and Process Engineering, Institute of Particle Science and Engineering at University of Leeds. Images were acquired with high magnification resulting in an effective voxel size of 3.64 μm using 225 kV and 300 μA current. A 6 mm × 6 mm surface was selected as viewing area. The samples were placed on the rotating stage and a number of two-dimensional (2D) X-ray projections were acquired at various angular positions. The projections were scanned at 0.15° increments for half of a full rotation i.e. 180°. At this rate a total of 1200 projections were acquired. Horizontal shadow images of the projections were reconstructed using a filtered back-projection algorithm.
Scanning and reconstruction time for each sample was about 3 h. In order to generate a stack of 2D cross-sectional images in a grey-scale format (256 shades of grey), the 2D X-ray shadow images were compiled using CT-Analyzer software. Volume data contains an incessant set of voxels that are organized in a 3D grid structure. The $x$ and $y$ axis represent the horizontal and vertical pixel coordinates (2D), whereas the $z$ axis characterizes the 3D spatial dimension [38].

### 3.3. Image Segmentation

The image post-processing algorithm was applied to 3D images using the MATLAB Image Processing Toolbox. Random noise reduction was achieved during image processing, by initial smoothing of the images using Gaussian filters. This was followed by segmentation where the volume is partitioned into voxel groups of solid i.e. fiber and void spaces. Segmentation is usually performed by means of thresholding technique. Voxels containing grey values lower or higher than this threshold value are regarded as background or sample material, respectively. This in return results in a stack of binary images in which each voxel is assigned to either the fiber matrix or the pore in the material [14, 39].

In order to improve thresholding accuracy, a local contrast enhancement procedure through histogram equalization was applied prior to thresholding. A log hyperbolic transform function that stretches the contrast levels further apart was applied. This procedure allows thresholding by using the mean intensity of the new image, which is fully explained by Pratt [40]. Figure 2a depicts the result of image segmentation step. The black and white pixels represent fibers and void space, respectively. Upon availability of the thresholded images, the 3D structure of nonwoven fabric can be prepared by stacking of thresholded images as shown in Figure 2b.

### 3.4. Skeletonization

Skeletonization provides an effective and compact representation of the image of an object by dimensionally reducing it to a “medial axis” or “skeleton” while preserving the topologic and geometric properties of the object [41]. In comparison to abundance of 2D skeletonization algorithms, only a few are available for 3D case, due to the following [42]:

1. 3D digital data was not readily available in the past.
2. 3D topological properties are laborious to address due to the higher dimensionality.
3. Useful applications of 3D skeletons were not defined.

In order to characterize spatial fiber orientation distribution of the 3D fibrous structure, the reconstructed fiber surfaces were first simplified to their medial axes or “skeleton”. In the present study the skeletonization algorithm developed by Yang and Lindquist [31] was employed. A brief overview of the technique and relevant terminology are presented here. Details of the skeletonization algorithm used in this work can be found in [42,43].

The skeletonization algorithm removes the voxel if [44]:

1. Voxel is a surface voxel.
2. Voxel is not end of line.
3. Deleting a voxel does not create hole.
4. Deleting a voxel does not change the number of connected component.

The output of above algorithm is a set of center lines, which is topologically equivalent to the original image and is one voxel wide.

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**Figure 2:** Schematic visualization of nonwoven fabric; (a) binary images; (b) 3D reconstruction.
When two fibers touch, the resulted digitized medial axis acquires a ladder-shaped containing substantial number of spurious paths. Using “surface remnant reduction algorithm” suggested by Yang and Lindquist [31], these paths are removed, provided their length is smaller than a fixed length threshold and their angular deviation from the fiber medial axis is greater than a fixed angle of threshold. Figure 3 schematically illustrates the surface remnant reduction algorithm. Figure 3a depicts two fibers i.e. green pixels intersected at an acute angle and the resultant ladder-shaped medial axis i.e. red pixels. Figure 3b depicts the medial axis after application of surface remnant reduction algorithm.

A 3D image of the medial axis of a sub-sample extracted from Figure 2 is shown in Figure 4. It can be observed that the medial axes bear a clear relationship to the original fiber surfaces.

3.5. Fiber Tracing

Segments with length less than a user specified value were deleted, based on assumption that such fiber can be result of noise in the input image. Fiber tracing was achieved by “Direct Tracking” algorithm proposed by Pourdeyhimi et al. [15] for measuring 2D fiber orientation with some modifications to measure 3D fiber orientation [31].

3.6. Orientation tensor

The orientation of an individual fiber in the 3D space was described by orientation tensor. Generally, the unique spatial orientation of a fiber is defined by two angles ($\theta_i$, $\phi_i$), alternatively it may be defined by a unit vector $p$ which is parallel to the fiber as follows:

$$p = \begin{pmatrix} \sin \theta \cos \phi \\ \sin \theta \sin \phi \\ \cos \theta \end{pmatrix}$$

Where $0 \leq \theta \leq \pi$ is the angle formed between the fiber axis and the z-axis, and $0 \leq \phi \leq 2\pi$ is the angle formed between the projection of the fiber on the $x - y$ plane and the $x$-axis.

A group of $n$ fibers can be described by the orientation tensor $a$, which is calculated by forming dyadic products of each individual fiber. The orientation tensor is calculated as follows:

$$a_{ij} = \frac{1}{n} \left( \sum_{k=1}^{n} p_i^k p_j^k \right)$$

The orientation of the network is quantified using the second-order fiber orientation tensor $a$ [45]:

$$a = \frac{1}{l_{tot}} \sum_{i} \left[ \begin{array}{ccc} \sin^2 \theta_i \cos^2 \phi_i & \sin^2 \theta_i \sin \phi_i \cos \phi_i \\ \sin^2 \theta_i \sin \phi_i \cos \phi_i & \cos \theta_i \sin \theta_i \cos \phi_i \\ \cos \theta_i \sin \theta_i \cos \phi_i & \cos^2 \theta_i \end{array} \right]$$

Where $l_i$ is the length of the $i^{th}$ fiber, $l_{tot}$ is the total fiber length and the sum is over the fibers that comprise the representative volume element (RVE).
The value of each of the diagonal values stands for the relative orientation around one of the coordinate directions. Since the distribution function is normalized and \( p \) is unit vector, the trace of \( a \) always is equal to unity, therefore:

1- For isotropic structures: \( a_{11} = a_{22} = a_{33} = 0.33 \)

2- For layered structures with fibers randomly oriented in \( x - y \) plane: \( a_{11} = a_{22} = 0.5 \) and \( a_{33} = 0 \)

2- For unidirectional structures with fibers oriented in the \( z \)-direction: \( a_{11} = a_{22} = 0 \) and \( a_{33} = 1 \)

Off-diagonal components points to orientation in bias directions. The orientation tensor is often defined as a symmetrical second rank tensor. This point to the fact that only six components of the orientation tensor are used:

\[
a = \begin{bmatrix}
a_{11} & a_{12} & a_{13} \\
a_{21} & a_{22} & a_{23} \\
a_{31} & a_{32} & a_{33}
\end{bmatrix}
\]  
(4)

4. RESULTS AND DISCUSSION

In order to evaluate the developed algorithms, 3D fibrous structures with pre-defined orientation were simulated using a Matlab base in-house developed computer software. Figure 5 shows the simulated nonwoven fabric. The described algorithms were applied to the simulated structure and the accuracy of algorithms was evaluated using Mean Absolute Percentage Error (MAPE):

\[
MAPE = 100 \times \frac{1}{N} \sum_{i=1}^{N} \frac{Y_i - P_i}{Y_i}
\]  
(5)

Where \( N \) is number of observations made, \( Y_i \) denotes the actual value and \( P_i \) represents the calculated value. The results indicated that that the algorithms appear to be extremely efficient in determining fiber orientation distribution in nonwovens.

The proposed algorithms were then applied to realistic nonwoven fabric. The calculated orientation tensor is presented below:

\[
a = \begin{bmatrix}
0.42 & 0.04 & 0.02 \\
0.41 & 0.01 & 0.17
\end{bmatrix}
\]

\( a_{11}, a_{22} \) and \( a_{33} \) are the measured fiber alignment in the \( x, y \) and \( z \) directions, respectively. Results point to approximate equality of \( a_{11} \) and \( a_{22} \) and negligence of \( a_{33} \). This indicate the high tendency of the fibers to align randomly in the fabric plane rather than be orient-ed along thickness of the fabric. The results also allow the test fabric to be ideally classified as a layered structure.

5. CONCLUSION

Nonwoven fabrics serve variety of end-uses such as thermal insulations, paper products, composite fabrica-tion, compact heat exchangers, fibrous filters and membranes. A thorough understanding and analysis of 3D structure and fiber orientation of nonwoven fabrics is quite challenging due to complexities and rando-mness of their structures. In depth understanding of these structures is enormously beneficial as far as pro-duct improvement, product performance and techno-logy development are concerned.

In this work 3D digitized images of nonwoven fabrics were progressively simplified by smoothing and thinning operations to produce an image in which fibers are represented by curves of one pixel in thickness. The 3D fiber orientation of nonwoven fabrics was then obtained by tracing and measuring the length and orientation of these curves. Orientation of fibers in the 3D space was described using the second-order fiber orientation tensor. The accuracy of proposed algorit-hms was assessed. It was established that, the results are not only accurate and reliable, but also can be applied to any nonwoven fibrous structure.
REFERENCES


http://dx.doi.org/10.1016/j.compscitech.2012.08.018


http://dx.doi.org/10.1016/j.powtec.2014.01.001

http://dx.doi.org/10.1016/j.earscirev.2013.04.003


http://dx.doi.org/10.1016/j.partic.2010.01.001

http://dx.doi.org/10.1063/1.4922607

http://dx.doi.org/10.1002/jbm.b.31389

http://dx.doi.org/10.1016/j.tifs.2015.10.016

http://dx.doi.org/10.1016/j.ijhydene.2012.08.077

http://dx.doi.org/10.1002/0471221325


http://dx.doi.org/10.1002/adem.200600033


http://dx.doi.org/10.1115/1.2796072