Computer Vision Algorithms for the Classification and Characterization of Fibers in Material Design

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Aimed to study the structure of materials acquired using micro computed tomography data, we resort to computer vision and machine learning techniques such as filtering, enhancement, and pattern classification to analyze 3D imagery of a ceramic matrix composite (CMC) sample reinforced by fibers. Our image work flow starts by transforming crops of image cross-sections (1200 curated images) using the normalization of pixel intensities to minimize intensity variations that lead to uncertain classification of fibers. We tested two classification approaches: the supervised LeNet architecture, and unsupervised hierarchical clustering. With the LeNet neural network, we perform classification of curated images into fibers and non-fibers. Next, we cluster the curated images with hierarchical clustering for the characterization of fibers, which provides insights with regards to taxonomy. Our results show that we can classify fibers with an accuracy of 98% by using 70% of the samples for training and 30% for testing. The clustering analysis points out to two main types of fibers: thin-coated fibers at the center of the specimen and thick-coated fibers in the outer parts. The merging of these computational processes helped us understand the false positives and false negatives, which are mostly due to the agglutination of fibers or very thin-coating. Future work includes exploring advanced feature extraction methods and tracking of 3D fiber structures in the entire image sequence.

The characterization of fibers is an essential component into the design process of new reinforced materials, as materials manufactures seek to ensure that its products are as per the specifications. To achieve high quality products, materials characterization at various stages is crucial; first at the chemical level to analyze their composition, then to analyze their thermal properties, and lastly, their physical structure and morphology, such as the parameters that govern the resilience of these fibers.

I. BACKGROUND

Ceramic matrix composites (CMCs) have become a material of choice for structures that withstand temperatures above 1,500^{o}C in hostile environments, as for example in the next-generation of gas turbines and hypersonic-flight applications[1]. The safe operation of new machinery depends on how small cracks forming inside the material are restrained by its micro-structure. In other words, enhancing CMCs with mechanical toughness is essential to avoiding failure[2,3]. When characterizing the fibers present in CMCs, scientists measure and probe their structure to aid in the design and engineering of these reinforced materials.

Reinforced CMC are permeated by fibers showing various 3D patterns, filled, and coated with specific elements to maximize their strength and as a consequence, minimize fiber deformation and failure. These composites ensure robustness through their complexity, as their hybrid micro structure prevents the growth of local damage and leads to the prevention of large cracks that are characteristic of brittle materials. Placing these composites under large loads or ultra-high temperature applications can trigger small cracks, whose propagation must be inspected before its deployment for use in the design of jet turbines[4].

As a way to quantify the failure of these materials closely, Micro-CT images have been used to scrutinized CMC samples with regards to crack paths, crack surface areas, orientations, spatial variations, crack-opening displacements, which are critical in the analysis of the material. This project outlines the approaches to study the composition of CMCs under loads and extreme heat exposure through the analysis of Micro-CT images using computer vision and machine learning algorithms.

II. MATERIALS AND METHODS

This project is composed of three steps: the acquisition of data and its curation, the application of computer vision techniques to enhance patterns of interest from images, and the use of machine learning algorithms for pattern classification. Merging these computational processes yields the complete framework necessary for an improved understanding of the composition of fibers present in CMCs.

A. Data acquisition and curation

The acquired 3D imagery is presented as an image sequence of 2390 gray scale cross sections illustrating the 2D interior of the CMC sample. Given the purpose of this project, it is essential to curate the data at the 2D level, to facilitate the careful analysis of the structure of fibers. Thus, we proceed to arbitrarily select a set of two images from the sequence to crop 16x16 pixels images

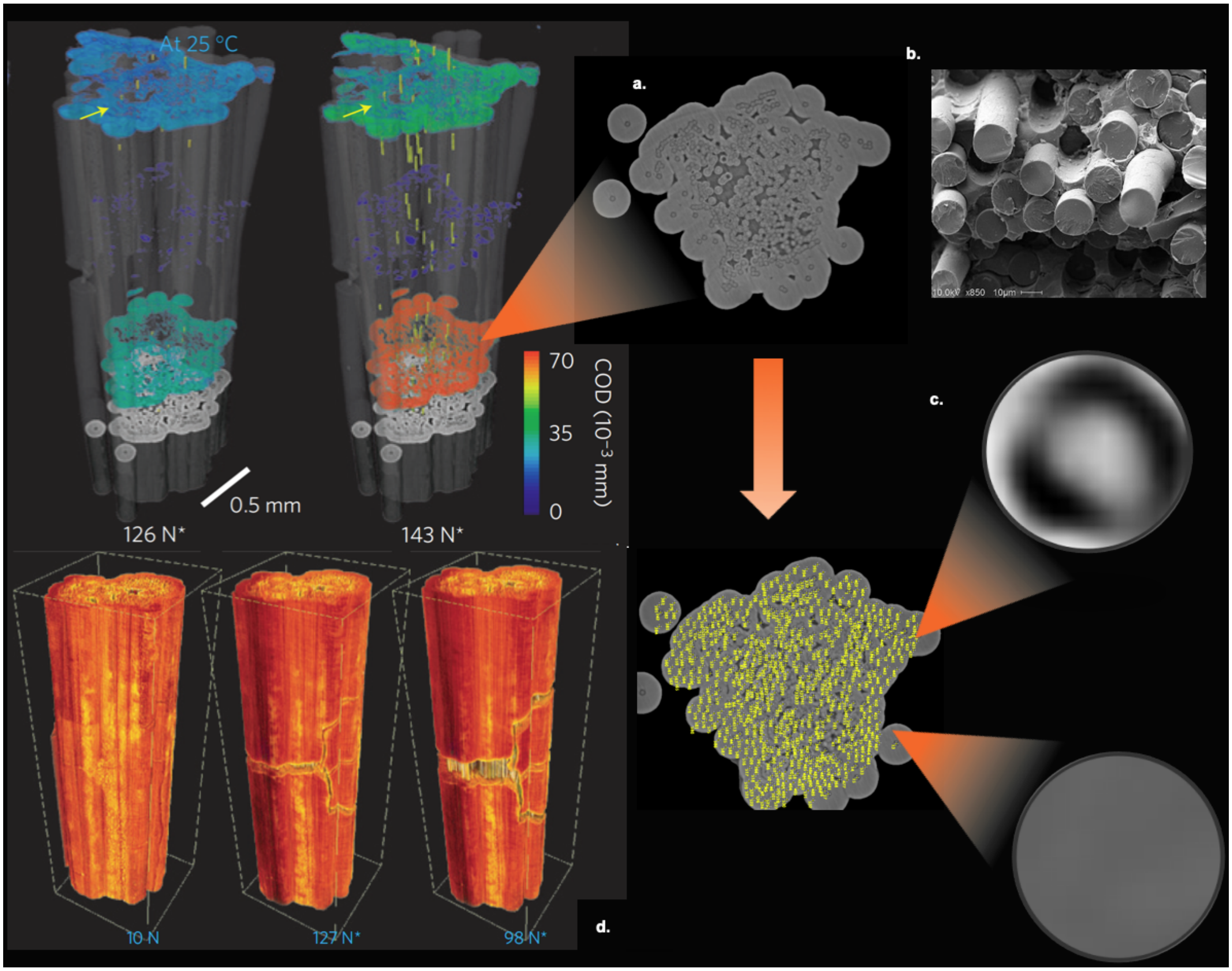

FIG. 1. Data curation process beginning with Micro-CT cross sections and ending with the manually generated crops of both fibers and voids. **a.** Crop-92: Micro-CT cross-section of CMC sample[4]. **b.** CMC electron microscopy[5]. **c.** Curation of the CMC cross-section depicting an example of a fiber and background. **d.** Quantification of cracks in matrix and fibers of Silicon Carbide composite specimens[1].

with ImageJ[6] software of fibers, voids, and backgrounds.

On each of the randomly selected images, (crop-92 and crop-171) we strategically select a total of 600 crops: 300 containing fibers located in the outer and middle sections of the CMC, and the remaining 300 consisting of voids and background within the sample. This process resulted in a set of 1200 crops containing 600 images of fibers and 600 images of voids or background [Fig. 1].

Throughout this project, the data set is to be handled as follows: We applied image preprocessing methods to all 1,200 images; the same amount was utilized for the training and testing of the convolutional neural network; and to compare algorithm performance, each of the two groups of 600 images from crop-92 and crop-171 were inputted separately in the clustering method.

B. Computer vision techniques

After the careful exploration of this new data set, we established the appropriate image processing techniques to enhance features essential for analysis. As a consequence of the location, placement, composition of each fiber, and the varying intensities of voids and backgrounds, we find that there is a large variability of pixel intensities in each cropped image.

With this diagnosis, we minimize these pixel discrepancies before the application of supervised and unsupervised machine learning methods by developing a data reduction scheme. We begin by transforming the crops of image cross-sections using the normalization (Equation 1) of pixel intensities in each image; a process which enhances the low contrast present in the data by spreading out the most frequent intensity values. Afterward, we proceed to standardize (Equation 2) the equalized intensities with the purpose of centering the pixel values in a smaller range of intensities.

$$X_{normalized} = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (1)$$

$$X_{standardized} = \frac{X - \mu}{\sigma} \quad (2)$$

C. Machine learning methods

The next step in our image work flow is to successfully distinguish the presence of a fiber from a background or void given any image cropping. Based on the success of this distinction, determine unique characteristics of the fibers present in the CMC sample. We achieve these goals through the testing of two classification approaches: a supervised LeNet[7] model, and unsupervised hierarchical clustering.

1. Supervised Model: LeNet-5 Convolutional Neural Network

With the high success rate of convolutional neural networks to classify image data, in addition to the relative simplicity of our cropped images for a binary classification, our architecture of choice follows that of the well-known LeNet-5. This network consists of a total of 6 layers: 3 convolutional, 2 average pooling, and 2 fully connected layers, with tanh and softmax as activation functions. Prior to inputting the images, we normalized all images to reduce the pixel intensity variability during the convolution operations. Of the 1200 crops, 70% were utilized for training, and the remaining 30% for testing; this resulted in an accuracy of 98% and a fast performance of less than 1 minute.

Table. I

2. Unsupervised Model: Hierarchical Clustering

Since the performance and accuracy of LeNet-5 provided encouraging results in the distinction of fiber versus background, much remained unanswered about the composition of fibers and how the data can be organized without training. Thus, in this section we focus on inspecting the composition of fibers from the results given by the unsupervised clustering algorithm. We turn to hierarchical clustering to take advantage of the dendrogram (tree diagram) produced after the clustering is complete to gain insight on how the sub-clusters are formed prior to the final binary classification.

TABLE I. Performance of LeNet-5 network.

Measure	Rates
Sensitivity	0.99
Specificity	0.98
Precision	0.98
False Positive Prediction Rate	0.18
False Negative Rate	0.01
False Discovery Rate	0.02
Accuracy	0.98

To enhance the performance of this method, we centralize and simplify the input data by applying both normalization and standardization techniques to the images. Additionally, we select the Ward[8] linkage method to minimize the sum of squared differences within clusters in the distance matrix prior to the generation of the dendrogram.

To compare the effectiveness of our data curation process, and since we want to retrieve information about each cross section given the image cropping, we run this clustering algorithm twice: first, with the 600 images from crop-92 and second, with the remaining 600 images from crop-171. Our confidence to achieve this goal increased after learning that we were able to preserve the order of the numbering from our strategic selection of image crops from each slice from section 1. This facilitates the visual analysis when comparing the images in each sub-cluster we describe below.

With the outputted dendrograms, we proceed to cut each diagram at a height where the final 2 classes branched out into 4 sub-clusters: two of these were classified as fibers, and the remaining as non-fibers. Afterward, we extract the image number from strategic process in section 1 to visually evaluate the false positives and false negatives in this clustering method.

The best resulting accuracy from this classification method was of 83%. But more importantly, from our visual analysis, we gained insight about the spatial distribution and thickness of fibers in CMCs. First, those false-negatives were fibers with thinner coating depicted as a lack dark pixel intensities in their edges, which made it harder to distinguish from the abundance of gray intensities present in voids and backgrounds. Additionally, these fibers were often agglutinated with other fibers with similar characteristics at the same location. Secondly, the fibers with thicker coatings and darker pixel intensities in their edges were often located in the outer parts of the sample, and were easily classified as fibers with a significantly smaller number of false positives.

III. RESULTS AND FUTURE WORK

With the successful curation of two cross-sections from the entire image sequence, we developed a new methodology to categorize fibers according to their composition and location in CMCs. Additionally, with the fast results of the LeNet-5 architecture we successfully distinguished voids and backgrounds from fibers with an accuracy of 98%. In the near future, we hope to combine these categorizing and classification methods with CAMERA (Center for Advanced Mathematics for Energy Research Applications) software to further analyze the design and structure of materials.

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