Technique of the identification, quantification and measurement of carbon short-fibers using the instance segmentation

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***Abstract*—The present work shows the use of a convolutional neural network architecture that uses the computer vision technique of segmentation of instances for identification, quantification and measurement of short carbon fibers.**

Keywords — carbon short-fibers, virtual training, instance segmentation, computer vision, convolutional neural networks, Mask R-CNN

I. Introduction

To generate a material model for reinforced polymers, it is necessary to extract a sample of the geometric characteristics of the fibers, this process is performed by analyzing images captured by electron microscopes [1, 2, 3, 4, 5]. The quality of the data, practically depends on the visual ability of the researcher, as well as the speed of data acquisition of the researcher's measurement skill. We have proposed to replace this task to people by a neural network, this through the use of deep learning techniques applied to computer vision. There are currently different types of convolutional neural network architectures that use various object identification techniques (object detection, semantic segmentation, instance segmentation, etc.) [6], [7], [8]. Within these techniques, the segmentation of instances in addition to detecting the location of the object of interest, can quantify the amount of this type of objects and group the pixels that make up each object. One of the main architectures to use the instance segmentation technique is Mask Region-Based Convolutional Neural Network (Mask R-CNN) [9].

Mask R-CNN was introduced in 2018 to extend its predecessor, Faster R-CNN, by the same authors. Faster R-CNN is a popular architecture for object detection, and Mask R-CNN extends it with instance segmentation. Mask R-CNN is a two-stage architecture: the first stage scans the image and generates proposals (areas that probably contain an object). The second stage classifies the proposals and generates delimiter boxes and masks [9]. Like other CNN architectures, Mask R-CNN takes advantage of learning transfer, which means that instead of training a model from scratch, you start with a weights file that has been trained on a predefined dataset, such as COCO. This allows the trained weights to have already learned various common features in the real images, which helps in the detection of geometric features [10].

II. Methodology

To get the Mask R-CNN to recognize the carbon short-fibers requires a large set of images captured in the electron microscope (see the Fig. 1) [11]. Obtaining a large and diverse set of tagged images is difficult because of the cost of image reproduction and the time of tagging the images. To solve this problem, the virtual image reproduction was resorted to with the help of assisted drawing software [12], [13], [14]. Currently, this solution is widely used because of the control of image characteristics and easy labeling of instances.

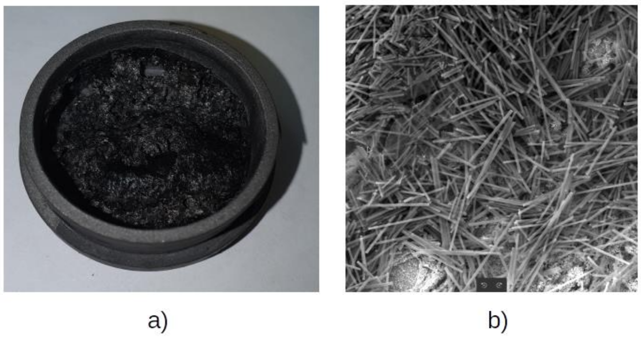
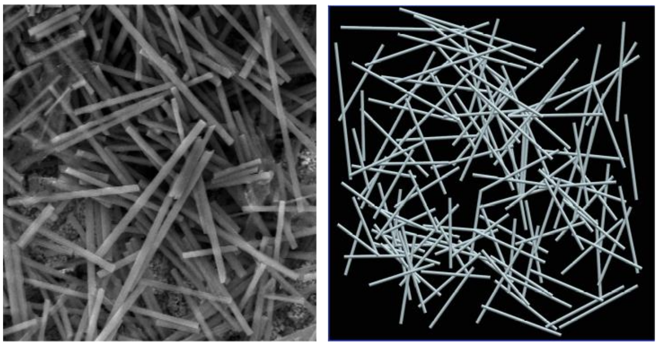


Fig. 1: Short fiber extraction from composite: (a) Sample preparation; (b) fibers after matrix burning

For the virtual creation of assembly images of short carbon fibers, the Siemens NX CAD software was used. The software contains tools that allow to simulate the texture and the effects of light and shadow as it is visualized in a real image captured by electron microscopy. NX Open is a collection of APIs for development of applications for NX. The APIs were implemented in a C programming environment for the creation of .dll files which are executed within NX for the creation of images, obtaining with this our virtual dataset [15]. The virtual dataset consists of a series of images, simulating randomly disperse fibers on a dark background, and a .json file corresponding to each image in which the coordinates of the fibers, within the picture, are stored.

In the first instance, in order to evaluate the performance of the Mask R-CNN architecture in the recognition and counting of short-fibers carbon, we started by using an image database (140 images) with a small number of fibers (10 – 16 fibers per image), and tried to distribute the fibers over the entire image area. A sample of images used for training, validation and testing of Mask R-CNN is shown in Fig. 3.

Mask R-CNN training was conducted under the following conditions: backbone option — resnet101; steps per epoch — 500, epochs — 30; learning momentum — 0,9; learning rate — 0,001; validation steps — 5; transfer learning by MS COCO; 60% of the images were used for training, 20% for validation and 20% for testing. The loss function is defined under the following criteria: loss for classification and box regression is same as Faster R-CNN; to each map a per-pixel sigmoid is applied; the map loss is then defined as average binary cross entropy loss; mask loss is only defined for the ground truth class; decouples class prediction and mask generation; and decouples class prediction and mask generation.



a) b)

Fig. 2: Real (a) and artificial (b) short fibers

III. RESULTS

An example of the performance of R-CNN for fiber recognition, counting and measurement is shown in Fig. 3.

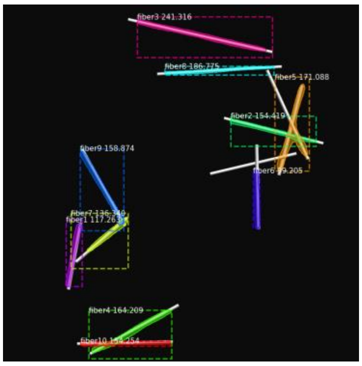


Fig. 3: Example of fiber count and measurement, values are in mm

Mask R-CNN highlights in different color the pixels corresponding to an individual (fiber), and taking advantage of the fiber location box, it is used to indicate the longest distance between different pixels corresponding to the same fiber to calculate the fiber length.

Fig. 4 shows the results of the case evaluated in the testing stage. It shows the accuracy at the time of counting the fibers and the accuracy at the time of measuring the fibers detected in each image.

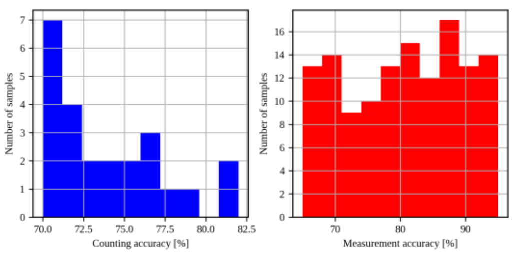


Fig. 4: Performance of R-CNN when counting and measuring short-fibers carbon in the testing phase

IV. CONCLUSION

In testing Mask R-CNN has so far demonstrated regular performance in identifying, quantifying and measuring short carbon fibers, for small assemblies, having 74% average accuracy when detecting and quantifying fibers, and 80% accuracy when measuring fibers. Although there are still big challenges to be solved, mainly to solve the part of detecting instances in very populated subgroups, due to the overlapping of the fibers, which prevents the fibers that are in the background to be difficult to identify their real size. Making an identification of these fibers by one person is difficult. At the moment the ability is to identify and measure the fibers at the top is more than sufficient to perform a statistical analysis on the geometric characteristics of the short fibers.

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