

Localization and extraction of centroids from composite materials
X-ray tomographies BROUILON

Mohamed Aymane Benayada

Thibault Leblanc

Kai-Wei Tsou

Julien Zhou

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Chapter 1

Introduction

Increasingly more composite materials are used in aeronautics, especially in engines. These materials are made of carbon fibers bundles which are weaved together within a resin matrix. It is essential, especially in order to reduce the cost of experimental studies, to determine or even predict the mechanical properties of these new materials thanks to numerical methods. Checking the weaving is necessary in order to discard parts with a defective weaving. Non destructive testing of aeronautic materials uses X-ray tomography to scan the structure of the material.

Currently, those volumes are analyzed manually and the centers of the bundles are annotated manually on a few slices. The remaining annotations are obtained through interpolations. This structure extraction step is currently essential for it allows to define the number of bundles to represent and to identify them to obtain their trajectory.

Manual annotations and interpolation corrections are time consuming and hard to get. To this day, the automation of centroid detection remains an open subject because of the complexity of image interpretation, especially when the bundles are weaved in a very compact way and that is impossible to distinguish them, without taking into consideration their configuration on neighboring slices.

In this project, our objective has been to try an approach to automatize the detection of bundle of fibers in X-ray tomographies. As getting annotated data is what we want to avoid, we based our approach on mainly unsupervised methods or methods with the least inputs from an external user possible.

In the following, we present the database and the way we preprocessed our images before introducing the methods that we implemented and discussing our results.

Chapter 2

Context

In this chapter, we introduce a formalization of the problem, the database that will be used in the following to test the approaches and a scoring methodology.

2.1 Problem

The overall objective of the project is to study approaches to automatize the detection and segmentation of different bundles of fibers from X-ray tomographies to retrieve their centroids, the far end objective being to implement a non destructive control procedure.

In fact, if we manage to get the centroids on each slice of the volume, and to link them between the slices, a 3D model of the material could be derived, which would enable to test the mechanical properties on numerical simulations.

Several classic image processing methods enable image segmentation, but they usually work with images with good contrasts and clearly defined edges, which is not really the case here as we will see. To account for that, we tried machine learning and deep learning methods.

2.2 Database

Safran provided us a volume of 1018 slices of 1024x1004 pixels images.

Visualisation of a few images....

In the few firsts and last images, we observed distortions in the images, so we decided to discard them (at least in the beginning). We kept the images from 150 to 850 (included), totalling 650 images.

At first view, it seems that the bundles of fibres often not clearly separated or clumped together in the images, we can assume that the main hindrance would be to find a way to separate those clumps.

2.3 Scoring: Aggregated Jaccard Index

We define here a scoring methodology that we will use in the following to evaluate the methods: the Aggregated Jaccard Index.

source

The Jaccard index, or Jaccard similarity coefficient, or Intersection over union is a metric used in statistics to compare the similarity between sets. For two sets of elements (in our case, it would be pixels), A and B , the Jaccard index $J(A, B)$ is defined as:

$$J(A, B) = \frac{|A \cap B|}{|A \cup B|}$$

This function returns 0 if the two sets have no element in common and 1 if they are identical.

We use a metric inspired from this index, an Aggregated Jaccard Index (AJI), enabling the comparison of different segmentations for unlabeled elements. Let's call G_i the ground truth sets and D_j the detected ones. The metric is computed as follows:

Algorithm 1 Computing the Aggregated Jaccard Index

```

Numerator  $N \leftarrow 0$ 
Denominator  $D \leftarrow 0$ 
for Each ground truth bundle  $G_i$  do
   $j \leftarrow \operatorname{argmax}_k J(G_i, S_k)$ 
   $N \leftarrow N + |G_i \cap S_j|$ 
   $D \leftarrow D + |G_i \cup S_j|$ 
  Mark  $S_j$  as used
end for
for Each segmented bundle  $S_k$  do
  if  $S_k$  has not been used then
     $D \leftarrow D + |S_k|$ 
  end if
end for
AJI  $\leftarrow N/D$ 

```

For each ground truth object G_i , we associate the segmented object S_j and add the pixel count $|G_i \cap S_j|$ to AJI numerator and $|G_i \cup S_j|$ to the denominator. Therefore, for ground truth fibers not detected, it only adds its pixel count to the denominator. And besides, the pixel count of all the unused detected element is added to the denominator count.

This index tackle the following errors: - Missed detection of ground truth annotated objects (pixel count in denominator increased) - False detection (unused S_k , pixel count in denominator) - Under-segmentation (the pixels are added several times in the denominator) - Over segmentation (several unused detections and small numerator VS big denominator)

Like before, the score is 1 if the segmentations are identical, and decreases if we are "far" from it.

Chapter 3

Image preprocessing

In this chapter, we present the methodology used to preprocess the images before the segmentation step. As written before, the firsts and last images of the volume show some distortions, therefore, we only took the images from 150 to 850 from the 1018 images provided.

We used the following process: - Trimming: in order to only keep the relevant part, - Denoising: we applied a first median filter to attenuate the noise, - Histogram Manipulation: to enhance the contrast of the image, - Denoising: to attenuate the potential noise from the last step.

3.1 Trimming

The part that interest us in the images is the center. Visu

The first step is therefore to separate it from the rest. We roughly extracted a rectangle in the middle of the image, containing the interesting part. Visu

3.2 Denoising

Blablabla

3.3 Histogram Manipulation

It is possible to increase the contrast of an image by adjusting its histogram. We explored 3 histogram manipulation methods: - histogram stretching - histogram equalization - adaptative equalization.

At the end, the method that we kept is the adaptative equalization.

3.3.1 Histogram Stretching

This technique improves the constrast by stretching the range of intensity to span the whole range of values. It applies a linear scaling to the image pixel values, and preserve the overall "shape" of the histogram.

To manage the outlier values in the histogram, we use the first and last percentiles instead of min and max values.

If c and d are the current values of the pecentile (let's say 2 and 98) of the histogram, and a and b are the desired min and max values (0 and 255), we have:

$$P_{out} = (P_{in} - c) \left(\frac{b - a}{d - c} \right) + a$$

Visu...

This operation improved the overall contrast in the image between dark parts (edges) and light parts (inner part of the fibers). However, the gap between the 2 intensity maxima is rather wide and it may be difficult to find an appropriate treshold for a global tresholding method for example.

3.3.2 Histogram Equalization

This method is used to increase the global contrast of images. It distributes the intensities by spreading out the most frequent values.

The method is a simple one and pretty straightforward, but a disadvantage is that it may also increase the contrast of the noise.

This method try to flatten the histogram of the image, and to change the cdf into a straight line.

Visu...

This method flattened the histogram. In our case, we can see that it has increased the noise a lot.

3.3.3 Adaptative Histogram Equalization

This is the method that we kept. This method differs from ordinary histogram equalization in the fact that it computes several histograms, each corresponding to a distinct section of the image. This method improves the local contrast and the definition of the edges in each region.

Visu...

The result show an enhanced contrast, with less noise amplification than with the global equalization. Besides, we kept the histogram structure with the two maxima corresponding to the inner and the edges of the fibers.

3.4 Annotations

In order to have a few ground truth segmentations, we manually annotated a few, using this soft found on githubhere.

VISU

We labeled 15 images equally distanced in the volume of 700 images.

Chapter 4

Segmentation

4.1 "'Classic"' image processing methods

There already exist several methods in image processing to segment images, mainly using the difference between different part of it to separate them. However, as we will see, they do not work very well on their own, mainly because of the fact that the edges are not clearly delimited.

4.1.1 Filters

4.1.2 Morphology

4.1.3 Watershed

4.1.4 Maximally Stable Extremal Regions

The idea is to exploit the evolution of regions using different thresholds on an image.

In fact, an increasing (or decreasing) thresholds on an image reveals growing areas of pixels that are below (or above) this threshold. The method consist in computing the area evolution rate of these regions and to consider that they are stable if this rate decreases. Therefore, this methods gives several "'stable"' regions on an image, and we can hope that they correspond to our bundles. However, this method need some tuning, notably the threshold changing rate, and we can use more informations like a bias on the area of the stable regions and their number.

Visu Equations

Chapter 5

"‘Advanced’’ methods

Our particular subject does not possess extensive litterature, but it has similarities with another one, the automatic cell detection on microscope images, which is more treated, and on which we concentrated our research.

The two mains categories of methods used in the litterature are roughly supervised and unsupervised methods.

In our case, supervised methods (dire les ref) has a huge drawback. They need a lot of already annotated data to train them, which is not really doable here.

For unsupervised methods, we are trying to get informations from the data without any training set, which is our case. In the case of deep learning an architecture enabling unsupervised training is an autoencoder (develop). We mainly looked at 2 autoencoders and implemented one for our tests. Another approach which could be promising would be to try to find a way to retrieve the missing edges, using for example the concavity of some curves in the image (cf...).

5.1 W-net

5.2 Sparse autoencoder

Chapter 6

Methods tried

We present here the methods that we actually implemented.

6.1 Maximally stable Extremal Region

We implemented the MSER algorithm as follows, adding a criteria on the minimal area of a component:

Algorithm 2 MSER implementation

Starting threshold $tresh_{min}$

Maximum threshold $tresh_{max}$

Threshold step $tresh_{step}$

Minimal area $area_{min}$

Set of stopped components $Stopped_{set}$

Current threshold $tresh_{current} = tresh_{min}$

We threshold the image and recover the connected components in $label_{current}$

while $tresh_{current} \leq tresh_{max}$ **do**

$tresh_{current} \leftarrow tresh_{current} + tresh_{step}$

 We threshold the image and recover the new components in $label_{new}$

 We link the new labels with the old ones

 We compute the new growing rate

 For all the new components, if the rate has decreased, we add them to stopped if the min area is reached
 otherwise we delete it

end while

Denominator $D \leftarrow 0$

for Each ground truth bundle G_i **do**

$j \leftarrow \operatorname{argmax}_k J(G_i, S_k)$

$N \leftarrow N + |G_i \cap S_j|$

$D \leftarrow D + |G_i \cup S_j|$

 Mark S_j as used

end for

for Each segmented bundle S_k **do**

if S_k has not been used **then**

$D \leftarrow D + |S_k|$

end if

end for

$AJI \leftarrow N/D$

6.2 Sparse autoencoder

Chapter 7

Results and discussion

We present here our results.

7.1 A few methods

7.2 Methods tried

7.2.1 etc

Chapter 8

Conclusion

Chapter 9

Bibliography

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