Automatic Composite Parts Defect Detector

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Both Computer Vision and Artificial Intelligence are acquiring an important role in the industrial processes, complementing human work to aid and improve the production of goods. In the aeronautic (and especially aerostructures) field, for example, it is crucial to determine as soon as possible whether a part of CFRP (Carbon Fiber Reinforced Plastic) is acceptable or not. Such a check is currently performed by hand at Aerostructure Division by qualified personnel who carefully analyse many parts images. This process is not only time consuming, but it can also introduce delays in the production process, causing great economic losses. To complement and relieve the human work, here an automatic method is proposed that performs image analysis to separate key carbon fibre layers from background, and performs defect detection by computing specific figures on the extracted components. Results are made available to the personnel, who validate the final output.

In the last decade, AI-enabled assisting tools have become more and more common in the daily life for aiding users in many ways. We find them inside smartphone applications that predict the user's behaviour or understand the environment to enable enhanced interactions. Recently the automatic recognition of an individual through his facial appearance has gained a lot of interest for both the end user and the big industries, helping the former to perform actions such as unlocking his smartphone, and enabling the latter to ensure, for example, that only allowed personnel do access restricted areas. Computer Vision is the field of study that makes use of visual sensors to analyse and understand the environment, allowing applications such as face recognition to be used by both the categories of end users mentioned above.
It is easy to understand that such a kind of technological development is not accepted so easily by industry, since it demands for stricter requirements. Being it pushed by its great success in many fields, CV has recently become a topic of interest for the industry too, which aims at leveraging new possibilities to complement and simplify the underlying industrial process.
In this work, we present a CV algorithm that automatically detects composite parts defects by analysing images of specific item. More specifically, this work aims at aiding qualified personnel in the process of understanding whether a part of a Carbon Fiber Reinforced Plastic (CFRP) in Leonardo Aerostructures Division is affected by a critical defect.
Currently the work is performed by the qualified personnel who must manually acquire and analyse images of each part of the CFRP-made structure and then decide about its acceptability by computing specific figures by hand on visually morphed parts of the image. This process is complex and time consuming. Also, it is often impractical to block the production chain that must go on even if it were not yet known whether the part in production will be then discarded or not. If the part ends up being not acceptable, it must be entirely disposed of, wasting a significant amount of time and resources. By using the CV algorithm to analyse the images, the qualified personnel is able to identify unacceptable parts since the earliest stages of the production chain and timely discard them, thus preventing from additional losses. Given the specific nature of the problem, the proposed method leverages the distinctive traits of the CFRP structure and separates the parts of interest from the background, by performing local brightness thresholding and connected component detection. Results are further processed to compute specific figures on each component, to understand its degree of distortion. They are then shown to the qualified personnel who always validate the output, allowing the needed high quality standards to be not affected by sporadic errors made by the module.
The module has been developed and tested on a small image dataset collected an Aerostructures Plant where it is to be used. Images without defects together with images with different degrees of defection have been collected with their relevant annotations regarding where the defection is and what its defectiveness figure.
The rest of the paper is organized as follows. First the related work is reviewed. Then the dataset is described and in depth details about the method are provided. Experiments and results follow and in the last section our conclusions are drawn.

RELATED WORK

Computer Vision, and Machine Learning in general, are becoming to play an important role at many industries'. We find it in Automotive, Healthcare, Agriculture, Banks and Shops. This phenomenon is often referred to as "Industry 4.0", or "the fourth industrial revolution". In this next step new technologies are introduced by industry to further enhance and automate its production processes.

As it has been studied in [2], the increase in computing power and the development of actively developed learning frameworks have caused sensible increase in research productions that have in turn stimulated the transition from Industry 3.0 to Industry 4.0.

The visual inspection of produced goods is one of the most common field for Computer Vision. Once a product completes a step along the production chain, it must be inspected by the personnel to ensure it reaches the given minimum quality standard. Computer Vision automates that kind of work by simply leveraging on images of the product. In [3], for example, the automatic optical measurement of an automobile component is performed. Various components are checked by first scanning a barcode to identify the product. A CV algorithm is employed to discover defects or damages.

For the medical production industry, [4] CV employs a set of cameras to monitor the production of syringes. Each part of a syringe is checked against production specifications and defective parts are highlighted on the user's application.

In the Agricultural business, [5] studies of in-field variations in corn plant spacing and population enable to better estimate the seed spacing while planting it. Crop images are compared against known samples by using correlation windows and the final images are threshold to extract and measure the space occupation of each plant.

In [6], a system to detect optical LED lenses is devised that uses block discrete cosine transform (BDCT), Hotelling statistics and grey clustering. Lens are checked for visual and dirt defects. The problem of understanding the state of construction of a building is studied in [7], where indoor images of buildings under construction are analysed to understand what the state of the construction process. To this extent, the algorithm helps detecting frames and insulation materials to estimate the progress of the works. Computer Vision algorithms are also employed in the industry to target the safety and health of employees. In [8], for example, a method to understand the hazard level of working environments is investigated. Thorough the use of multiple cameras, LIDARs and stereo cameras, 2D and 3D data are acquired and used to understand unsafe acts and conditions, unsafe acts based on location and movements of project entities and identify violation of safety and health rules regarding motions. The textile industry [9] uses Multi Resolution Combined Statistical and Spatial Frequency (MRCSF), Markov Random Field Matrix method (MRFM), Gray Level Weighted Matrix (GLWM) and Gray Level Co-occurrence Matrix (GLCM) for automatic detection of defects in fabrics. The kind of defect is also detected.

Finally, in [10] a comprehensive survey is presented, analysing both inspection techniques and inspected product. For inspection techniques, both the filtering-based and the learning-based approaches are studied.

As for most of the previous methods, we employ a filtering-based Computer Vision algorithm for the task of automatic composite parts defects detection. Our choice is motivated by two reasons: the lack of a big collection of annotated images to train a neural network with, and the simplicity of the devised filtering-based approach. In fact, the algorithm consists only on a smoothing pass, followed by an adaptive brightness thresholding and a morphological noise removal step.

TASK AND DATASET

In this section, the task of composite parts defect detection is first introduced. The current acquisition and validation protocol is then illustrated and finally it is described how the dataset used to study the problem has been collected.

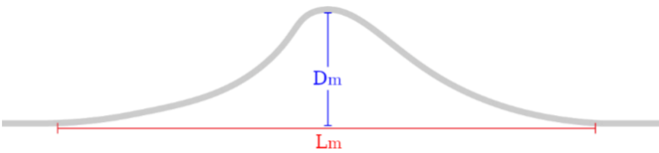

Figure 1 – Dimensions of a wrinkled ply

Composite Parts Defect Detection Task

The large composite parts of an airplane produced in Aerostructures Division consists of multiple sections produced by stacking flat layers of carbon fiber resins, called plies, which are then given the desired shape. This last operation can introduce in specific and well-known parts of the layers, some wrinkle shaped deformations or distortions that, depending on their severity, can lead to structural damages, which of course must be avoided.

The wrinkle severity figure is one of the factors that play an important role in deciding whether a whole section can continue the production process or it cannot. Such figure is computed as follows:

$$wrinkle\ severity\ factor = \frac{Lm}{Dm} \qquad (1)$$

where Lm and Dm are the width and height dimensions respectively of the wrinkle. Figure 1 shows how these figures are measured with respect of a given wrinkled ply. The lower is the wrinkle severity factor, the higher the risk of it suffering structural damage. Studies have defined a specific threshold under which the ply is considered "wrinkled" because it is affected by a high severity deformation, and as such the whole part it belongs must be discarded.

The task at hand is to first identify and extract all the different plies in a given image and second to measure the wrinkle severity for the wrinkle that may, or may not, be present in the last (bottom) ply. As it is explained in the following paragraph and can be seen in Figure 2, not all the plies are equally visible in the acquired images. Here we focus only on the recognition of the more visible, which from now on is referred to as the *bright* ones.

Acquisition and Validation Protocol

A large part of at an Aerostructures Plant can be produced in many versions and each version, for example, has two sides:

forward side and aft side. Depending on the part-version-side combination there are specific locations where multiple images have to be acquired. For each location at least 3 images are taken. Depending on the section produced, the acquired images of each section can vary between 150 and 300, which must be all analysed.

The acquisition is currently performed by using a 5Mpixel hand-sized USB microscope that produces images with 1280x960 pixels resolution. Images are then saved in the JPEG format by the producer proprietary acquisition software. The acquisition process produces a number of images similar to the one shown in Figure 2. Here we can distinguish the different CFRP plies, along with the deformation present around the middle part of the last ply.

Figure 2 – Example of acquired image

Qualified personnel then has to analyse images - one at a time - and manually compute the wrinkle severity figure, to determine whether the part is allowed to continue the production chain or it must be entirely discarded. This process is currently performed by first measuring width and height of the wrinkle on the screen by using a virtual ruler, that is by selecting a starting and an ending point onto the image. The software outputs the estimated measure between the points. Then the Figure is manually computed and results are drawn on the original image by using an image editing software. Figure 3 shows the measure result for the same image shown in Figure 2.

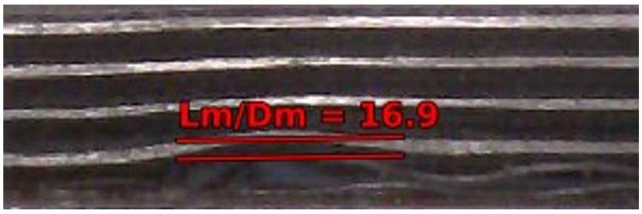

Figure 3 – Example of wrinkle severity annotation

This validation protocol suffers from several pints of weakness. It lacks accuracy, since the exact location of the points used by the virtual ruler can slightly vary between operators. It takes time to perform a single measurement, as it cannot be carried out directly on the part during acquisition. Off-line measurement is performed on only 3 images per location in case more than 3 have been acquired; this process is as well carried out by hand.

Dataset

Images such as the one in Figure 2 are normally acquired and are stored at the Aerostructures Plants by qualified personnel, every time a new part enters the production chain. We leveraged this database to create the dataset used to depict the CV method and to test its performances. The database consists of tens thousands images but, thanks to the high quality standards of the production chain processes, only a small fraction exhibits defects important enough to be measured and labelled by the qualified personnel. Labels consist of the *Lm* and *Dm* measures that are necessary to compute the wrinkle severity figure. From this subset, a subset of images is extracted with different degrees of defection (both under and above the critical threshold) and images with no defection or with level of distortion so low that have been deemed not to be critical even with not any need for measuring it through the manual measurement process. Moreover, images have been acquired from different locations of specific part selected.

METHOD

As described in the previous paragraph, the annotated dataset is composed by a small number of images due to the intrinsic nature of the problem. For this reason, a Deep Learning approach was not feasible since data were not enough to perform the training of the network. A simple but yet effective classical CV approach was then devised which is composed of two parts. The first part, the ply extraction, analyses the image to recognize the bright plies; the second part, the distortion measurement, computes the distortion Figure 6 or a given ply.

Preprocessing

The images obtained with the previously described acquisition process may contain other content that the plies to measure. Such content must be removed before they undergo the automatic measurement process by “cropping out” everything that is not related to the plies.

Ply Extraction

The algorithm proceeds as follows:

1. the image is first converted to black and white and filtered using a Savitzky-Golay [1] smoothing filter to remove image quality impurities;
2. the smoothed image is thresholded by using a local variable threshold where each pixel is compared against the mean of its local window;
3. small impurities are removed by applying the morphological operators of *opening* and *closing*;
4. *bright* plies are isolated by looking for connected components that have a pixel area bigger than a given minimum threshold;
5. if present, the last ply is taken into consideration and is passed to the measuring algorithm. An example result of this phase is shown in Figure 4.

Distortion Measurement

Distortion measurement is performed once the *bright* plies have been isolated in the image, for a single selected ply. The algorithm proceeds as follows:

1. find the leftmost and rightmost coordinates of the lower

contour of the ply;
2. compute the segment between those two points and compute the respective angle, as shown in Figure 5 (top);
3. if the angle is below a threshold compute the distance between the lower contour and the segment;
4. find the longest sub-segment that has distance greater than 1 pixel and set its length as the *width* dimension to compute the final Figure 1 and set the maximum distance of the sub-segment from the bottom contour as the *height* dimension to compute the final figure, as shown in Figure 5 (bottom);
5. set the *wrinkle severity* Figure 1 as the ratio of *width* and *height* dimensions.

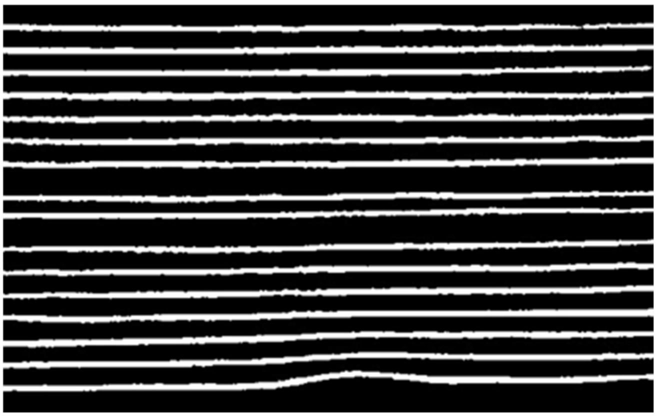

Figure 4 – Example result of ply extraction

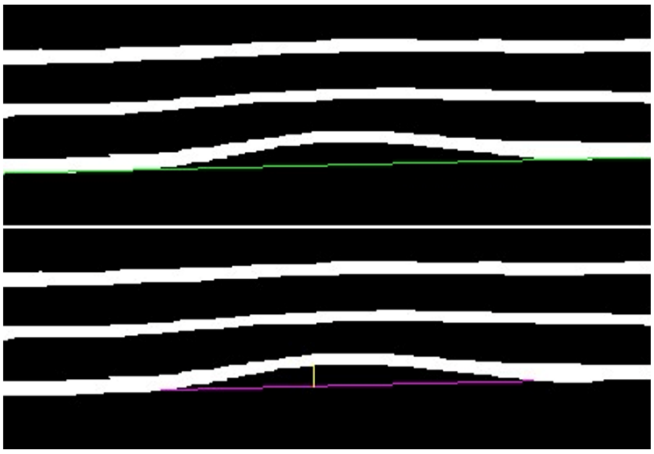

Figure 5 – Example of the distortion measurement process: (top) baseline detection; (bottom) width and height measurements

The resulting Figure is then drawn on the input image and shown to the operator as in Figure 3. If at any point of the algorithm, some conditions are not met, for example if no ply is found during the ply extraction phase or the segment angle computed during the distortion measurement phase is over the predefined threshold, the operator is warned so that manual measurement can still be performed. This precaution is fundamental to preserve high-quality standards, preventing from leaving anomalous cases not measured.

EXPERIMENTS

This paragraph reports on the qualitative experiments performed on the small dataset we described in the Task and Dataset section.

Since our method does not require any training, the whole dataset has been used to evaluate qualitatively the proposed method. Here qualitative results are shown of the ply extraction phase and the distortion measurement phase. The wrinkle severity Figure is impressed on each image.

Four cases are reported that are shown in Figure 6, G, H and I, with different degrees of wrinkle severity.

Figure 6 shows a relatively small wrinkle that is correctly detected by our method. The ply extraction phase correctly detects all the bright plies and the distortion measurement phase measures the wrinkle severity correctly. Only the third *bright* ply from top is not recognised, due to contrast attenuation on the right end.

Figure 7 shows another successful example where the wrinkle severity is more pronounced. The ply extraction phase extracts most of the bright plies. Again, the missing ones are the ones for which the contrast level becomes very low around edges of the image. The distortion measurement phase is again able to measure correctly the wrinkle severity, even with more than one wrinkle on the ply. This is an expected behaviour and is a direct consequence of the distortion measurement algorithm. In fact, the algorithm measures the length of the wrinkle that is relative to the baseline of the whole ply. In this example, the more severe wrinkle is the one that distorts the ply the most and features the longest sub-segment distance.

In Figure 8, the bright plies are all detected correctly during the ply extraction phase. The distortion measurement phase performs an almost prefect measure, but due to the image suffering from slight blur effect, the sub-segment width results a little shorter than it should be.

Finally, in Figure 9, an unsuccessful case is reported, in which the ply extraction phase is not able to detect correctly the last *bright* ply due to very low contrast zones in the wrinkle location. The method is able to recognise this case and does not perform any measurement. The qualified personnel is informed and can perform manually the same measurement.

CONCLUSION

This work proposes a method to detect automatically defects in large composite part. The presented method leverages on Computer Vision techniques to analyse images of specific locations of the parts. It is able to first detect and extract each of the brightest carbon fibre layers the parts are made of. It then analyses the lower most bright layer, to detect the presence of a wrinkle defect and to extract a severity measure related to the detected deformation. The result of such processing is made available to the qualified personnel, who however are always responsible for validating the results obtained. Moreover, failure cases are detected and reported to the user.

To depict the method, a dataset of images from the database of already collected acquisitions in an Aerostructures Plant has been first created. Then the method has been developed and tested on a subset of that dataset, to perform experiments aimed to validate the predicted wrinkle severity.

Due to the nature of the problem and to the relatively small

size of the dataset, a local brightness thresholding and its connected component detection method has been developed instead of a Neural Network based method.
Results show the successful approach of such a method that provides good estimation of the wrinkle severity figure in most of the tested cases. Even in case no wrinkle is detectable, the qualified personnel are informed and the measure can be performed manually.

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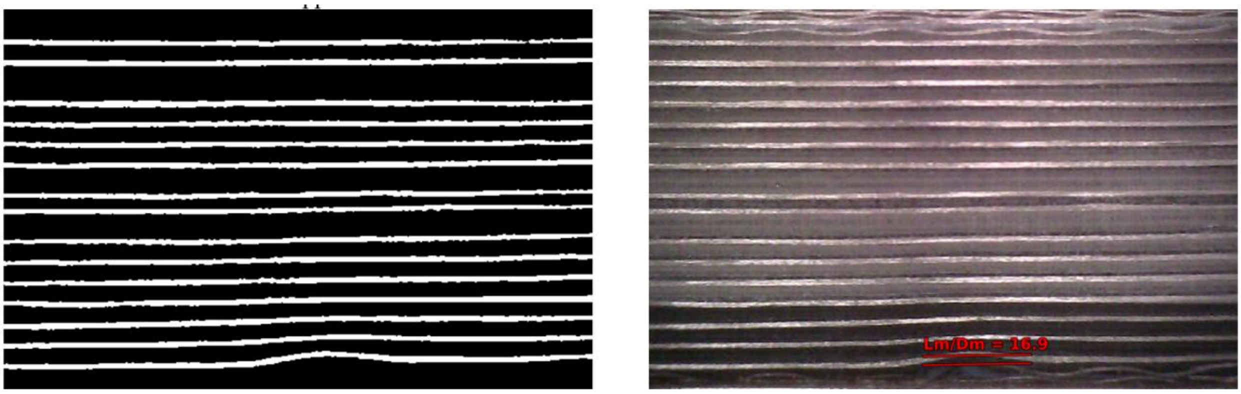

Figure 6 – Correct measurement of the wrinkle severity figure

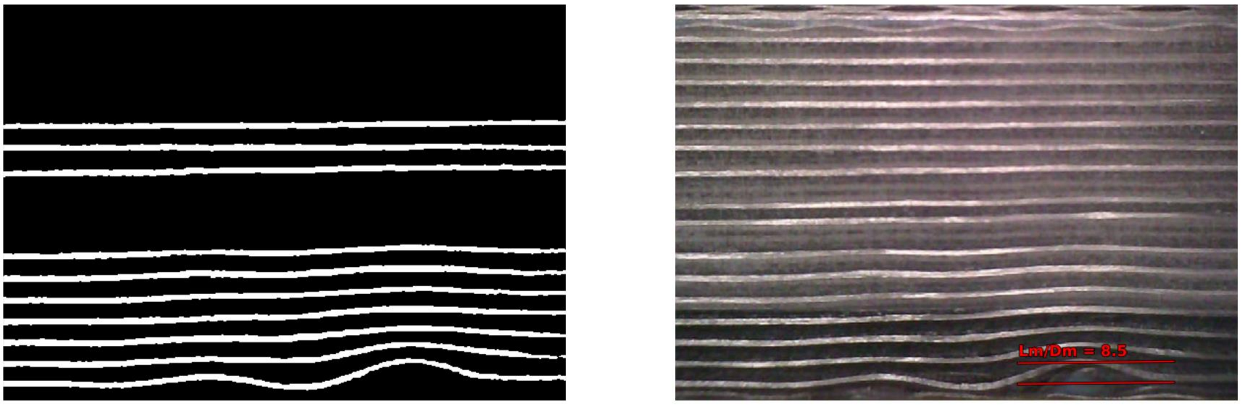

Figure 7 - Correct measurement of the wrinkle severity figure when more than one wrinkle is present

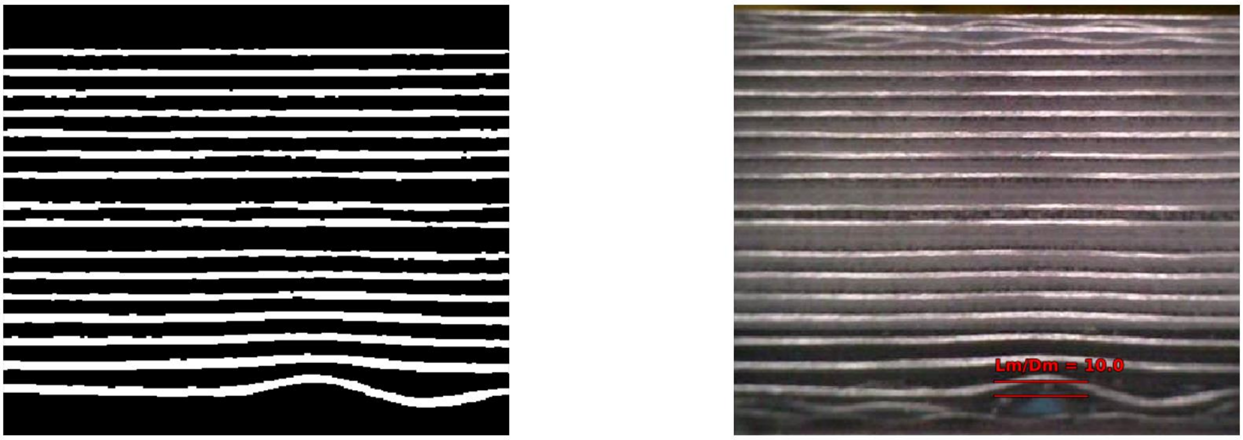

Figure 8 – Incorrect Measurement of wrinkle severity on a blurred image

Figure 9 – Incorrect detection of last ply. Wrinkle severity Figure is not performed in this case

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