Detection of Filament Misalignment in Carbon Fiber Production Using a Stereovision Line Scan Camera System

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Abstract. The performance of carbon fiber semi-finished products as well as all follow-up products is largely dependent on the quality of the carbon fiber rovings. During carbon fiber production various defects affecting quality may occur. Whereas numerous defects such as fuzz balls or roving twists are easy to identify, other fiber fractures remain a challenging defect for inline detection. Such filament fractures are to be recognized during the production process as superficial misaligned filaments. The detection of misalignment however must lie within the scope of a filament width, where a typical carbon filament diameter lies within the order of 5-7 µm in contrast to 2-3 m during fiber mass production. This requires methods of area detection with a resolution in the order of the single filament diameter.

Based on the above, the current study focuses on the image processing (described below) and the integration of a camera system along the production line. Due to the required high image resolution, large scan width and current production line speed, image processing as well as the image acquisition requires adapted approaches for the in- and online evaluation.

To maximize the scan width a stereo vision line scan camera system is included in the production line. The software processes the stereovision camera information for image segmentation from two different angles. As a result, there are two images, a rectified and a disparity image, describing in and out of plane data respectively. The algorithm scans the single lines of the rectified image and transforms the image into a gradient image. The approach searches for connected components that lie within a grayscale range. These areas most likely describe filament misalignment and foreign particles / contaminations.

By this we obtain a system able to support the visual inspection by highlighting regions of interest (ROI). With the resolution in the order of a few microns, defects from the filament fractures and small foreign particles up to fuzz balls can be clearly marked. This information forms the basis on which patterns are derived for an automated classification of several defect types. A challenge however remains the statement related to the volumetric amount of defects, since current techniques do not allow the online detection at such required resolution, production speed and width.

1. Introduction

As the structure carrying the main load, the carbon fiber is mainly responsible for the performance of the semi-finished products as well as the reinforced plastics. The performance...
of carbon fibers is on one hand limited by a spectrum of microscopic flaws like particles, voids and surface fractures within the fibers, which have been examined and reported back to the late 1960’s [1-3]. But these defects, which are driven by the precursor quality and the production process, can usually only be detected under laboratory conditions. On the other hand macroscopic flaws like fuzz balls, roving twists and filament fractures lead to additional performance loss.

Macroscopic flaws usually occur in later production stages, either on roving level or on semi-finished products like non-crimp fabrics (NCF). On roving level the hairiness is typically obtained using photoelectric barriers or monitoring the scattered light caused by optical diffraction on the edge of emerging filaments [4, 5]. Vision systems are applied on textile structures as NCF or woven fabrics. This allows to monitor the fiber orientation, gaps between fibers, fuzz balls as well as so called fish eyes or knitting errors (both for NCF) [6-8]. Anyhow, the performance of a carbon fiber reinforced plastic (CRFP) is driven not only by its components, resin and fibers but also by the quality of each of them. Therefore, the focus in the presented work is set to the quality monitoring within the fiber production, before it enters the spool winding.

![Fig. 1. Carbon fiber production process based on PAN precursor [9]. Additional marks, show the spots of inspection considered within this paper.](image)

The observed carbon fiber production process is based on polyacrylonitrile (PAN) precursor Fig. 1. The PAN precursor is provided on coils or folded within a box. Either way, the precursor is spread onto the continuous transport mechanism. The first step is the oxidation or thermoset process. The precursor is heated up to a temperature between 200 – 300 °C to stabilize the precursor for the upcoming carbonization process. During the carbonizing, the fibers are heated above 1200 °C in an inert atmosphere. After the carbonization follows surface treatment and sizing until the final spool winding. [9, 10]

From precursor to sized carbon fiber the optical characteristics vary extremely. Starting with a relatively thick white PAN-fiber at position 1 to a non-conducting black fiber after the oxidation, a thin dull black fiber after the carbonization resulting in a shiny thin black sized fiber.

With the position and the change in the optical behavior also the visibility and the frequency of the typical flaw modes vary. By monitoring and quantifying the defect modes, information about the process stability and the quality of the carbon fibers can be obtained. The challenge in addition to the changes in optical behavior is the required resolution to detect the smallest defect e.g. the single filament fracture of a carbonized fiber, maintaining the online capability as well as a reasonable scan width.

With the work at hand, Fraunhofer ICT-FIL demonstrates an online applicable monitoring system to categorize and quantify defects from the more macroscopic level like fuzz balls down to single filament fractures.
2. System layout and experimental setup

As the conditions at hand are a continuous moving target with poor optical behavior, e.g. weak texture, poor reflective properties and a minimal defect size with 5-7 microns a matrix camera system would not be the system of choice. Due to the fact that the required exposure time would lead to blurred data, the little lateral resolution compared to a modern line scan camera would also require a high amount of cameras to monitor the full production line width (which may be up to several meters).

2.1. Camera system

The selected camera is a stereo vision line scan camera system offered by the company Chromasens\(^1\). The 3DPIXA stereo line scan camera is a type C01-015-0040 camera, with a resolution of 15 microns and a scan width of 40 mm. The vertical resolution is about 3 microns.

![Fig. 2. Basic principle of the stereo vision line scan camera system.](image)

The stereo vision principle is based on two images captured from the same object with a distinct variation in the angle of view. In the present case this is realized by a lens system mapping the information on a line detector as illustrated in Fig. 2. Via triangulation and pattern matching algorithms the elevation profile of the captured structure is calculated in real time on the graphics processing unit (GPU). As a result, an elevation profile as well as the color images are available for further calculations.

![Fig. 3. System setting - consisting of an illumination system, the camera and a personal computer with a frame grabber and a dedicated graphic processing unit.](image)

The complete system setting used for the integration in the carbon fiber production line requires additional components. The system setting is shown in Fig. 3. In addition to the camera, an illumination system (consisting of illumination and controller unit) and a PC with a frame grabber and a dedicated GPU are required. The camera sends a continuous stream via Camlink to the frame grabber. Here the data is split into single frames which can be processed by either the GPU or directly by the application software.

2.2. System integration

As a result of the triangulation principle, the geometric configuration and the high resolution, the depth of field is limited to only 2.5 mm. In front of a deflection pulley, usually a part of

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\(^1\) Chromasens GmbH is a developer and producer of machine vision components. Typical products are line scan cameras, spectral cameras, 3D stereo cameras and LED illumination systems. The company is located in Konstanz, Germany. For detailed information look at: www.chromasens.de
a transport mechanism, the fibers are spread and the vibrations are limited. Along the carbon fiber production line, transport mechanisms are integrated between the different process steps. These areas usually provide enough space to integrate camera and illumination. Therefore, these locations are the preferred installation positions as no interferences with the production line and process are necessary.

Table 1. Three different material conditions are considered along the production process. Every material stage requires adopted image capturing and later data processing parameters.

<table>
<thead>
<tr>
<th>Material condition</th>
<th>PAN precursor</th>
<th>oxidized PAN</th>
<th>Carbon fiber</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fiber color</td>
<td>white</td>
<td>black</td>
<td>black</td>
</tr>
<tr>
<td>Fiber surface</td>
<td>glossy</td>
<td>dull</td>
<td>glossy</td>
</tr>
<tr>
<td>Illumination</td>
<td>dark field</td>
<td>diffuse incident light</td>
<td>diffuse incident light</td>
</tr>
</tbody>
</table>

In this paper, three different material conditions will be considered more closely: the PAN precursor prior to the oxidation process, the stabilized precursor after the oxidation process and the carbon fiber captured directly after the carbonization process. Depending on the position, the illumination arrangements as well as the intensity are adopted to the optical characteristics of the fibers at hand.

As mentioned above the scan width with the 3DPIXA is about 40 mm. Therefore, only a single spread roving is monitored at once. To obtain different states, changes in precursor, process parameters as well as the lateral position of the monitoring system have been examined. The resulting data was then manually investigated and the defects were counted and classified as reference for the automated detection.

2.3. Flaw categorization

As mentioned in the introduction, the presented solution is capable of detecting defects from the macroscopic range like fuzz balls down to fiber fractures in the micron scale. Therefore, a categorization of different types is needed. The presented classes are based on the most frequently observed deviations from regular structure during the experiments.

Fig. 4 shows the appearances of fiber fractures in two different material states during carbon fiber production. They both need a look on the micron scale and appear on a small amount of pixels in the image. However, both are characterized by one soft end appearing to emerge from the well-structured roving and another hard end with a sharp drop in intensity value. Although there is a slight difference in the defect characteristics for the oxidized PAN fibers, the same categorization is applicable.

Fig. 4. Occurrence of fiber fractures in the oxidized (left) and carbonized condition.
Typical flaws observed within carbon fiber: loops (left), loose filaments (center) and fuzz balls (right).
Occurrence is similar on fibers in oxidized condition.

Fig. 5 shows three additionally observed defect types. The left one is a so-called ‘loop’ named after its appearance, beginning and ending in the roving plain with a loop in-between. A loose filament is illustrated in the middle. It typically forms a fixed angle against the predominant direction of the roving and no specified start and end. The largest and most obvious defects are fuzz balls, as shown in Fig. 5 on the right, consisting of a group of randomly oriented filaments. On PAN fibers, an additional defect type can be found (not shown here). So called ‘dots’ are round contaminations on the roving surface, showing a typical round bright characteristic spot on the measurement system output.

Table 2. Characteristic elements of different defect types used for categorization.

<table>
<thead>
<tr>
<th>Characteristics</th>
<th>Filament fracture</th>
<th>Fuzz ball</th>
<th>Loose filament</th>
<th>Filament loop</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dimension in x</td>
<td>small</td>
<td>high</td>
<td>high</td>
<td>small to medium</td>
</tr>
<tr>
<td>Dimension in y</td>
<td>small to medium</td>
<td>high</td>
<td>small to medium</td>
<td>high</td>
</tr>
<tr>
<td>Number of pixels</td>
<td>small</td>
<td>high</td>
<td>medium</td>
<td>medium</td>
</tr>
<tr>
<td>Angle</td>
<td>small deviation (in moving direction)</td>
<td>Undefined / multiple orientations</td>
<td>negative or positive orientation</td>
<td>negative and positive orientation</td>
</tr>
<tr>
<td>Change in gray value</td>
<td>high</td>
<td>small</td>
<td>small</td>
<td>small</td>
</tr>
<tr>
<td>Deviation of gray value</td>
<td>small</td>
<td>high</td>
<td>high</td>
<td>high</td>
</tr>
<tr>
<td>Gray value maximum</td>
<td>medium to high</td>
<td>high</td>
<td>high</td>
<td>high</td>
</tr>
<tr>
<td>Gray value minimum</td>
<td>high</td>
<td>small</td>
<td>small</td>
<td>small</td>
</tr>
</tbody>
</table>

In summary there is a variety of defect types during carbon fiber production. However, effects of defects in carbon fiber production are not entirely clear. Focusing on the mechanical performance of the resulting carbon fiber roving, fractures most likely have a significant impact. Although the origin of loops, loose filaments and fuzz balls are not completely evaluated, the main focus of detection and categorization is on fiber fractures. To identify single defects, at least one unique characteristic peculiarity is needed for each type. Table 2 shows different characteristics evaluated for automated categorization. Depending on material and investigation spot a calibration is needed. Every value is then determined throughout image processing.

3. Data processing and evaluation

In this chapter, the overall workflow for data processing will be presented in detail. Depending on the camera system and the position within the production process, the specific execution of data collection and evaluation varies.


Table 3. Main workflow of data processing from image rectification to defect classification.

<table>
<thead>
<tr>
<th>Activity</th>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rectification</td>
<td>Creating an image projection</td>
<td></td>
</tr>
<tr>
<td>Preprocessing</td>
<td>Combination of filters prepares image for further analysis</td>
<td>Trace connected intensity areas in a series of image lines</td>
</tr>
<tr>
<td>Filtering</td>
<td>Intensity tracing in 3x3 window</td>
<td>Separating areas with potential defects, removing artefacts from data; collecting data for classification</td>
</tr>
<tr>
<td>Defect counting</td>
<td>Particle extraction</td>
<td></td>
</tr>
<tr>
<td>Classification</td>
<td>Determining defect type</td>
<td>Refer defect to a category, determining a typical fiber fracture</td>
</tr>
</tbody>
</table>

At first, input data from the camera is transferred to the frame grabber in a stream of lines. The number of lines that are captured by the grabber in one cycle before forwarding it to the computer can be set in the driver settings. Initially, the input data is available in 24 bit RGB quality. The stereo camera acquires two separate images of the same region from two different angles as shown in Fig. 2. The images are then rectified which is carried out using the CS3D API provided by Chromasens. A major part of the rectification process is executed on a dedicated GPU, which allows the CPU to merely focus on data processing tasks. Keeping in mind the real time requirements, this is a major feature that comes with the hardware. As a result of the computation, the images are color matched and optical distortions are corrected.

Based upon the rectified images the disparity image for the 3D information is calculated. For the rectification process as well as the disparity image calculation, the API by Chromasens GmbH provides algorithms that are specifically designed for their camera systems.

3.1. Image preprocessing and segmentation

Before analysis operations can be applied to the image, in many cases morphological filtering is necessary. In order to identify the best choice, a series of filters is used. Some were able to highlight defect areas. After morphological filtering was applied the tracking of connected structures is taking place. Further information on this procedure is presented in the following sections.

3.1.1. Image enhancement using morphology and equalization

Since image acquisition depends on system adjustments and can vary according to illumination, foreign particles and camera positioning, degradation in the image quality occurs in some cases. Surface reflections partially proved to be too homogenous, so deviations in the structure or even single filaments could not be extracted from the image when using the original and unhandled data. Common methods are non-linear filters such as dilatation, erosion, opening and closing [11, 12].

These methods, commonly known as morphological operations, change the shape of objects in the image [12]. Elements that stick out in size, intensity or orientation will be even more highlighted, since dilatation thickens them [11]. This effect can pay off later when further processing is applied in order to find derivations in the filament structure.

Furthermore, under certain illumination conditions, the image histogram might show a concentration of single gray values in a small range which usually results in lower contrast. Further analysis would then less likely find the defects, since differences in gray values are
the most important feature for the computer vision system. By applying histogram equalization, the image quality can be improved significantly, since the histogram will be stretched to use the full spectrum of the gray scale [11].

3.1.2. Image enhancement with Gradient and Sobel operators

Fiber cracks and similar defects tend to show a noticeably high intensity in images. This effect can be used in the detection process. Among different filtering techniques, edge detection algorithms proved to isolate these structures. For contours with steep gradients on both sides, the Sobel operator provides very promising results. Therefore, the nonlinear Sobel operator was used to analyze the input image data. For detailed information see [12]. Even for edges with low gradient profiles, Sobel can help to identify these elements. As seen in Fig. 6, single filaments fractures are visible when applying edge detection with the Sobel operator.

![Fig. 6. Same scene on both images, where on the right side is the single filament fracture is detected and segmented.](image)

The results after applying a Sobel based edge detection and region extraction on input images will be discussed in the following chapter. So far, the computer vision system was able to automatically identify areas that show unanticipated characteristics that can potentially influence the fiber consistency. The anomalies shown in this paper cannot be seen with bare eyes as it has often been attempted in production processes so far.

3.2. Defect extraction

After finding edges in the image data, regions of interest (ROI) must be identified. The ROI must be separated and divided into sets of pixels that potentially contain defects. Each ROI will be checked for artifacts. If no critical or only single pixel defects are found, these areas will be removed from the list if necessary. Otherwise the area is extracted from the original image and temporarily stored in the memory. This area is then converted into a binary image snippet and written to a file, if the classification process proves it to be a real defect. The classification is further explained in 3.3. The approach can be summed up as follows:

- Each ROI is checked for artefacts and removed from the defect list, if parameters do not apply.
- A defect area is then extracted from the processed and filtered image.
- A binary snippet will be kept in the memory and written to a file, if the classification process proves it to be a real defect.

3.3. Classification

After defect extraction, each ROI must be classified as a defect according to the definition of an artefact. The data is compared to either training data or put through a chain of logical states, a network or a statistical test method. This will help to remove false positives, artefacts and abnormalities that will not interfere with the production process. This has not been
examined in details within this study. However, some of these techniques are currently examined and can help to improve results.

4. Results and Discussion

The defect recognition rate varies with the optical characteristics of the material, changing over the production process. Even though, the defect types as well as the defect occurrences change with the material stage and type at hand. As far as it affects the defect detection, a homogenous structure as well as minor local gray value deviations are advantageous. As this is true for the PAN precursor and the carbon fiber, for the images acquired of the oxidized PAN fibers it is not. Accordingly, the following results concentrate more on the PAN precursor and the carbon fiber stages, as for the oxidized PAN additional investigations are required.

![Fig. 7](image)

Fig. 7. Filament loops as well as a loose filament in the middle. Crosswise to the fiber direction the segmentation is working. Parallel to the fiber direction the deviation of the gray values is too little for sufficient detection.

The defect detection and segmentation are exemplarily demonstrated in Fig. 7. As can be seen the detection for filament loops and loose filaments is working. Fuzz balls typically consist of loose filaments and can also contain filament loops as well as filament fractures. As a detailed segmentation of the fuzz balls is not appropriate, larger areas affected by multiple defects are identified and counted as fuzz balls as seen in Fig. 8. The system also proved to be able to identify filament fractures as already shown in Fig. 6.

![Fig. 8](image)

Fig. 8. A fuzz ball and some loose filaments in one spot. For a reliable classification appropriate distinguishing features have to be identified and adopted to digital processing.

The quantification as a result of the segmentation process is more difficult as artifacts have to be filtered and connecting structures be identified. Therefore, the recorded data was automatically segmented and counted. Afterwards a visual inspection with support of the automated segmentation was carried out and the defects logically classified. In Fig. 9 the results for two different PAN precursor are compared. The diagram shows the relative distribution of defects between the two precursor and the comparison of automatic and visual
supported inspection. The investigated length was the same for both precursors. The absolute amount of all failure types between the two precursor is in the order of 2.5 to 3.

Fig. 9. Relative distribution of defects counted with digital support as well as using automatic inspection for two different PAN precursors. While on PAN 1 no filament fractures were found additional contamination (dots) were detected.

In Fig. 9 a distinct difference between the two precursor is obvious. Especially the amount of fuzz balls and loose filament differ. The failure “dots” only appears on PAN 1, while filament fractures only on PAN 2 were observed. The filament fractures at the PAN 2 were detected reliably but the quantity compared to loose filaments or the other failure types was very little. The software supported inspection leads to a reduction in the overall amount of failures due to the fact that separated loose filaments could visually be closed.

The same investigations were conducted on the carbon fibers. In this case the carbon fiber production was carried out with two different sets of processing parameters, while the precursor was maintained. The defect “dots” was not investigated on the carbon fibers but filament loops were added to the failure modes. As illustrated in Fig. 7 filament loops usually were detected as loose filaments, due the fact the segmentation parallel to the production direction is more complex. Therefore, a high amount of automatically detected loose filaments and a low count of filament loops was expected while after the visual supported inspection this should shift. Compared to the images captured of the precursor the contrast ratio of the carbon fiber images is very low, as a consequence more segmented artifacts occur. Typically, these artifacts differ from the observed failures in an indefinite geometrical form. With visual investigation usually the artifacts can be assigned to the relevant failure modes. Nonetheless, optical or digital artifacts cannot be eliminated completely.

Fig. 10. Relative distribution of the different defect types. The absolute count between both settings is in the order of 60 %. The major defect type are loose filaments.

As mentioned above, the predicted behavior, reduction in loose filaments and increase in filament loops, was proved. Furthermore, the artifacts result from the little contrast ratio and could be nearly completely classified with visual inspection. In Fig. 10 the relative distribution of the defects for both parameter settings is illustrated. The absolute
count between both settings is in the order of 1.6 for the automatic segmentation as well as for the visual inspection.

5. Summary and outlook

As demonstrated in this paper, the detection of failures as fuzz balls down to filament fractures is possible. Based on these results, the next steps of the system development will be addressed shortly.

To transfer the application from laboratory scale to industrial use, the scan width has to increase. This is already in development by increasing the sensor area as well as by a parallelized image capturing of neighboring scan areas with a single camera system. In consideration of the real-time requirements, a default computer set with limited hardware performance could be a critical issue. For this case, basic operations could be outsourced to FPGA hardware. Either for an increase in measurement width or in resolution, this might become inevitable due to the high amount of data generated. Additional features will mainly address the detection and characterization of flaws by the implementation of further filter and detection algorithms as well as curve approximation procedures to increase the classification reliability.

When applying a set of filters, there is usually a critical number of artifacts that occurs in the processing of the image. In order to remove false information automatically, there are different strategies that can meet these requirements. First of all, there are supervised methods that usually require training data. Typical representatives are support vector machines or decision trees. Although supervised algorithms can be optimized until they show a high level of reliability, it is often the less preferred solution, since creating useful training data is often a time-consuming and difficult task. Unsupervised and self-adaptive concepts follow the idea of fully automated systems and gain more popularity in recent studies [13, 14]. These concepts comprise artificial neural networks, clustering, Bayesian networks or latent variable models. Also the physical and logical limits of object detection and image processing must be taken into account, when high performance systems are implemented as discussed in this paper.

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References


