Autonomous visual detection of drilling-induced defects in CFRPs based on digital image processing

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Research Article

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Abstract

Carbon Fiber Reinforced polymers (CFRPs) are critical kind of materials in many industries due to their superior mechanical and physical properties. However, the pivotal mechanical process of CFRPs is considered to be drilling, which easily leads to CFRPs defects including burr and delamination. Although substantial CFRPs defect inspection methods have been suggested, the user-friendly measurement of CFRPs defects and fast measurement speed are still challenging. To this end, a digital-image-processing-based method for identifying and measuring the drilling-induced defects in CFRPs specimens is proposed. By comparing with the manually measured results, it shows that the proposed method can accurately (the maximal relative errors are separately 5.76% and 3.42% for burr factor and delamination factor) and quickly (4 s per micrograph) recognize and measure CFRPs defects. Moreover, the method has no requirement for adjusting any parameters manually and shows strong robustness to the interference from the bright noise. Based on above, the method is anticipated to provide a meaningful reference for recognizing and measuring CFRPs defects in large quantities.

1. Introduction

Carbon Fiber Reinforced Polymers (CFRPs) exhibit attractive mechanical properties, such as high specific strength and high specific rigidity, heat and corrosion resistance, and therefore have wide application in both aerospace and automobiles [1–3]. For most CFRPs products, the mechanical drilling would be the indispensable mechanical manufacturing process during the assembly process [4]. More importantly, CFRPs are difficult to process and tend to generate some defects (including burr and delamination, see Fig. 1) due to the nature of carbon fiber and laminated structure. Many experiments have proved that those defects greatly reduce the strength and fatigue resistance of CFRPs materials, thus not only having a negative effect on the usability of CFRPs products, but also being harmful to the accuracy of assembly between CFRPs components. Hence, to detect and evaluate CFRPs hole-exit damages, many researches have been reported so far.

In order to prevent the defects during image acquisition or detection, some non-destructive detection methods such as ultrasonic C-scan, Computed tomography (CT) are adopted. Sugita et al.[5] used ultrasonic flaw detector to observe the internal defects and fiber pull-out of drilled holes. Apart from ultrasonic detection method, Haeger et al.[6] used CT to take radiographs, followed by adopting the image processing software to process the radiographs and determining the delamination factor. The above mentioned detection methods due to their strong penetration ability, high sensitivity, have shown good performance in the inspection of the drilled hole defects. However, these methods have not been widely used in detecting CFRPs defects with the limits of the professional equipment and controlled environment.

To choose a suitable method in defect detection, vision-based detection is proposed in many research articles, which is considered to have quick, accurate and low-cost characteristics. The visual detection method is usually equipped with optical microscopes or digital cameras. Region of interest (ROI, here are
the defects areas) of the captured images is generally extracted and analyzed by digital image processing. Stone et al. [7] used CCD camera and visual digitizer to capture the drilled hole images. The delamination was monitored by an acoustic emission system of the neural network control scheme. Meanwhile, Faraz et al. [8] utilized a stereomicroscope with specialized lighting to observe and measure the delamination areas of drilled holes. These captured photographs were processed by the ‘AnalySIS’ software to quantify the delamination. Gaugel et al. [9] used an optical microscopy and three different illumination concepts to quantify three different defect phenomenons in the edge of drilled holes. To further improve the accuracy of the defect detection, some novel detection technologies were introduced. Hrechuk et al. [10] proposed a complicated modular digital image processing method to extract the delamination and burr. The findings showed effective and accurate detection results of delamination and uncut fiber, but it takes up to 3 min to run the program for each drilled hole. Maghami et al. [11] proposed a camera device equipped with four LED lights to enhance the visibility of the defect features from four directions. Besides, a method based on a deep Fully Convolutional Network (FCN) with the U-Net architecture was applied to detect and segment the CFRPs hole defects. The results showed excellent performance in detection accuracy (the maximum error is only 5.4%) and time of detection (less than 1s per image), while there needs the support of substantial datasets. Although the results of these methods show the efficiency and availability of visual detection method, there still has the possibility of improvement. Moreover, due to the similarity of visual features between material texture and defect areas, and the random fiber longitudinal distribution of defects, the proposed image processing method should have strong robustness and high automation to detect defects easily [12].

In view of the importance of accurately detecting the drilled hole defects, this paper attempts to improve algorithms of the proposed image-processing-based method to automatically recognize and quantify the defects. Therefore, a novel comprehensive method for automatically recognizing and measuring defects (including delamination and burrs) based on digital image processing is proposed. The proposed method can be summarized into three major parts, including image pre-processing, defects extraction and defects evaluation. Especially in defects extraction, a peak detection segmentation and K-means segmentation are proposed to extract defects area respectively, which do not require adjusting thresholds and presetting any parameters. The evaluation results measured by proposed method are all compared with the manual measurement, which could prove the accuracy and robustness of the proposed method. The method can be expected to be meaningful and helpful for the measurement of defects in CFRPs in large quantities and the application of the CFRPs products.

2. Proposed Methodology

2.1 Flowchart:

Figure 2 shows a flowchart of the proposed methodology to detect defects of CFRPs. The burr is located on the inner side of the drilled holes, while the delamination is on the outer rim in general. Thus, areas of two defects are analyzed respectively. To achieve a robust and accurate measurement of burr and delamination, the methodology mainly contains three key steps, including: (1) Recognition of the profile
and area of burr, ( ) Recognition of the profile and area of delamination, ( ) Evaluation of the drilled holes defects. The following proposed algorithms used the OpenCV library in Python to implement.

## 2.2 Recognition of the profile and area of burr

The optical pathway inside drilled holes has minimal reflections due to the use of low-angle lighting when taking micrographs[13]. Therefore, the drilled holes are usually the dark region separating from other regions (see Fig. 3). The profile and area of burr can be obtained by extracting the profile and area of drilled holes. As seen in Fig. 3 (a-h), the detailed procedures are as follows:

( ) Considering the purpose of the proposed method is to automatically detect CFRPs defects in large quantities, the captured micrographs are converted into the gray images (see Fig. 3b), which could improve the speed of detection.

( ) Due to the similarity of visual features between noise and defect area, the noise will influence the results of image processing, so image filtering is required. Figure 3 (c) separately gives the filtering results by using three classic filtering algorithms including mean filter, median filter, and Gaussian filter. It clearly shows that the median filter could remove noise effectively. With a 3*3 kernel size of median blur, the pixels covered by the kernel are ordered from smallest to largest, and then take the median of all pixels in the kernel instead of the pixel in the center of a kernel. The noise could be removed to improve image quality.

( ) From Fig. 3 (d), it can be seen that the captured images have bimodal histograms. To separate the area of drilled holes from the micrographs, a method based on adaptively locating the thresholds on the minima between the histogram peaks is used. First, get all “gray levels – Number of pixels” coordinate points in the histogram and connect them into curve. The first minima on the curve is set as the threshold. Because the curve connected by these coordinate points is not smooth enough, it cannot accurately judge whether the first minima of the curve is the pixel value at the trough. To solve this problem, one-dimensional Gaussian filtering is employed to smooth the curve, and the gray level of the first minima, the desired threshold, can be accurately determined by the argrelextrema function in Python (see Fig. 3e). Then, the micrographs are binarized using captured thresholds with two values, 0 (black) for the background and 255 (white) for the region of drilled holes (see Fig. 3f). Finally, the cv2.fillPoly function in OpenCV is applied to fill small noise region.

( ) Fig. 3 (g) shows the burr profile (blue) extracted by applying the cv2.ndContours function and the information of all profile points can be obtained. Then, cv2.MinEnclosingCircle function is applied to obtain the minimum enclosing circle of drilled hole (nominal hole) using the information. The area of burr is shown in the Fig. 3 (h).

## 2.3 Recognition of the profile and area of delamination

After the recognition of burr, the part of delamination is detected by the following steps:
( ) Considering the opposite distribution of two defects, the region of burr should be excluded in this process. Therefore, the nominal hole defined by previous step is set as the mask, and then the region of delamination is processed independently. After masking the region of burr, the micrographs mainly include three parts: area of delamination, area of nominal hole (mask) and other area (see Fig. 4a).

( ) Then the K-means segmentation is adopted to segment the delamination. Here the K-means segmentation method is based on Ref[14, 15]. Rather than calculating the threshold from the final partition, the segmentation result is determined by the number of pixels of three classes (i.e. three parts mentioned in step ( )).

Let \( f(x, y) \) denote the input pixels at the position \((x, y)\). Considering reducing calculation amount, the input pixels are given normalization (see Fig. 4b). Therefore, The image with resolution of \( N = m \times n \) can be presented by a data matrix:

\[
l(x, y) = \frac{f(x, y)}{256},
\]

1

\[
[F(x, y)]_N = [l(x, y)],
\]

2

Hence, randomly select three centroids \( c_k (k = 1, 2, 3) \) from the normalized pixels in \([F(x, y)]_N\). The method assigns the pixels to the nearest centroid based on the Euclidean distance \( d \):

\[
d = ||l(x, y) - c_k||,
\]

3

After the assignment of all pixels, new cluster centers \( c_k \) for each cluster are recalculated below:

\[
c_k = \frac{1}{k} \sum_{y \in c_k} \sum_{x \in c_k} l(x, y),
\]

4

Repeat the process until the positions of the cluster centers no longer change. Therefore, \( N_{del}, N_{nom}, N_{other} \) respectively refer to number of pixels in area of delamination, area of nominal hole and other area. It can be found from Fig. 4 (a) and (c) that according to the size of order, \( N_{del} \) has the fewest number of pixels. Thus, the class of the fewest number of pixels is the target class (i.e. class of delamination). If the pixels are owing to the target class, the gray levels of the pixels are set as 255, if not, the gray levels are set as 0.

Figure 4 (d) presents the result by performing the K-means segmentation method. A defined threshold based on area size can remove the remaining small noise (see Fig. 4e).
The next step to identify the delamination is to extract the contour of delamination. Firstly, the coordinate values of all pixels in the image (in the Cartesian coordinate system, see Fig. 4(f)) that are classed as delamination pixels are obtained, and then they are converted into polar coordinates, as shown in Fig. 4(g). The transition can be expressed as Eq. (5), Eq. (6) and Table 1:

\[ x_i = i - x_{\text{center}}, \]

\[ y_i = j - y_{\text{center}}, \]

Table 1 Coordinate transformation of points in the 4 quadrants

<table>
<thead>
<tr>
<th>Polar</th>
<th>Cartesian</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \theta )</td>
<td>( \frac{180^\circ \cdot \arctan(y_i, x_i)}{\pi} )</td>
</tr>
<tr>
<td>( r )</td>
<td>( \sqrt{x_i^2 + y_i^2} )</td>
</tr>
</tbody>
</table>

Where \((i, j)\) and \((x_{\text{center}}, y_{\text{center}})\) respectively denote the coordinate position of the pixels in the micrograph and the center point of drilled holes in Cartesian coordinate system. Thus, \((x_i, y_i)\) refers to the coordinate position of pixel \((i, j)\) after moving the Cartesian origin coordinate to the center of drilled holes.

In the polar coordinate system, the pole is the center of drilled hole, and the ray \( ox \) from \( o \) is the polar axis. The positive direction of polar coordinate system is set to be clockwise, which is same as the scanning direction (see Fig. 4h). With \( 1^\circ \) interval of the polar angle, the polar coordinates of all pixels on the ray in this angle are obtained. After obtaining all polar coordinates on 360 rays along the circumstance, a scatter plot is drawn (shown as Fig. 4i). If there have pixels of delamination (i.e. the white pixels in Fig. 4h) at this angle, the pixel with the longest polar radius in the delamination region at this angle is obtained. While if there has no pixel of the delamination region at this angle, the polar radius of the pixel at this angle is set as the drilled hole radius. In this example, the drilled hole radius is 255 pixel. The connecting line of these pixels is the contour of the delamination (see Fig. 4j), and Fig. 4 (k) shows the result of recognition of the contour of delamination.

### 2.4 Quantification of CFRPs defects

After recognizing the CFRPs defects, they need to be evaluated. To date, multiple methods have been approached for quantifying burr and delamination in former researches. For burr damage, burr factor \( F_b \) is the most commonly used evaluation criterion. It is calculated as expressed in Eq. (7)[16, 17] and shown in Fig. 5(a), (b) and (c)[18].
where $A_{nom}$ denotes the nominal area of drilled hole, $A_{free}$ represents the burr-free area of drilled hole, and $A_b$ is the burr area.

For delamination defect, the most conventionally used delamination evaluation criterion is the delamination factor $F_d$ proposed by Chen. The delamination factor $F_d$ is defined as the ratio of the maximum circle diameter $D_{max}$ to the nominal drilled hole diameter $D_{nom}$, which can be expressed as Eq. (8)[19] and illustrated in Fig. 5 (d)[20].

$$F_d = \frac{D_{max}}{D_{nom}},$$

The above two convenient evaluation criterions $F_b$ and $F_d$ are very useful for a fast quantification. Therefore, in this study, $F_b$ and $F_d$ are used for the evaluation of drilling-induced damages. The pixels of nominal hole and drilled hole are used for extracting $A_{nom}$ and $A_{free}$ respectively. In addition, the minimum enclosing circle of the drilled hole and the mask are used for calculating $F_d$.

3. Experimental Work

In this section, experimental drilling trails of CFRPs were performed and the defect micrographs of drilled holes were captured to validate the method.

3.1 Fabrication of the CFRPs workpiece

The CFRPs laminates were fabricated from 40 layers of plies which were made by the carbon fibers impregnated with the epoxy resin. The orientations of single-layer fiber were $0^\circ$ and $90^\circ$ respectively. The workpiece used in the experiment had a length of 100mm, a width of 80mm and a height of 8mm(see Fig. 6d). Details about the fabrication procedure of CFRPs laminates are as follows: ( ) Calculate the requirement of carbon fabric and resin on the basis of the resin volume fraction of CFRPs laminates; ( ) Glue each layer of carbon fabrics together with an adhesive film, which is made by melting the resin and evenly coating it on the impregnated paper, so that the fiber fabrics can adequately soak in the resin to make prepreg plies; ( ) Cut and place prepreg plies in the mold; ( ) Apply the hot press at the temperature of 85 ℃ for 0.5h and then 130 ℃ for 0.5h; ( ) Complete the demold and trimming process of the CFRPs workpiece[21, 22].

3.2 Experimental setup
As shown in Fig. 6 (a) and (b), all drilling experiments were implemented on the G-VM5 CNC vertical machining center (Guangzhou Machine Tool Factory, China), which has a maximum spindle speed of 6000 rpm and a maximum feed rate of 3500 mm/min. The HSS twist drills are widely used in the industry due to their excellent attributes and low cost. In this experiment, the HSS twist drill with a point angle of 118° and a diameter of 6mm produced by AOBEN Company was employed (see Fig. 6c).

The drilling parameters employed in this experiment are given in Table 2, and a series of trials were carried out. Besides, the depth of cut was 8 mm and 29 holes were drilled in equal spacing.

To verify the accuracy of the proposed method, the evaluation results of the drilling defects separately calculated by the software ImageJ and the proposed method are compared. To avoid accidental errors, the manual results of each group of trials are measured three times. Besides, massive micrographs with various degrees of defects are employed in the comparison.

<table>
<thead>
<tr>
<th>Group</th>
<th>Spindle speed (v_s) (rpm)</th>
<th>Feed rate, (v_f) (mm/min)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2000</td>
<td>60, 90, 120</td>
</tr>
<tr>
<td>2</td>
<td>3000</td>
<td>60, 90, 120</td>
</tr>
<tr>
<td>3</td>
<td>4000</td>
<td>60, 90, 120</td>
</tr>
</tbody>
</table>

### 3.3 Acquisition of the hole micrographs of the CFRPs workpiece

After the CFRPs drilling experiment, an Annular-light and Black-background image acquisition setup (see Fig. 7a) was designed to complete image acquisition of CFRPs drilling-induced defects. The lighting device consists of a LED flexible Rope Light wound in a ring, which can illuminate from all directions of drilled holes. Due to reflective areas on CFRPs surface, the low-angle lighting was used to highlight undulating surface defects more effectively. In addition, a black background cloth was employed to enhance drilled hole feature (see Fig. 7c). All micrographs of drilled holes were captured by an optical microscope (Leica SAPO, Germany). Figure 7b gives the captured typical micrograph of the drilled hole, where defects appearing as white region after feature enhancement can be clearly observed in contrast to the color of the CFRPs workpiece.

### 4. Results And Discussion

#### 4.1 Measurement accuracy
Figure 8 shows burr factor and delamination factor comparison between the manually measured values (see Fig. 8a, d, g, j) and the values calculated by the proposed method (see Fig. 8b, e, h, k). Among these figures, the micrographs with superscript 1 and 2 are the measurement results of burr, while the micrographs with superscript 3 and 4 are the measurement results of delamination. The results (see Fig. 8c, f, i, l) present a reasonable agreement between the manually measured values of burr factor and delamination factor and the values automatically obtained by the proposed method. Among several groups of the comparative results, the maximum relative error of burr factor is 5.76%, while for the discrepancy of the other three groups are all smaller than 3%. In addition, the relative errors of delamination factor are all about 3%. The results prove the effective and accurate defects measurement of the proposed method.

4.2 Speed and Automaticity of Measurement

To automatically recognize the profile and area of defects and measure $F_b$ and $F_d$, especially for a large number of detection tasks, the detection speed of the proposed method needs to be evaluated. The method coded by Pycharm software is employed to recognize and measure both burr and delamination for all micrographs given in Fig. 8 (a1–l1) (the employed PC is InterCore i7-8750H 2.20GHz). It takes around 4s per micrograph to obtain all results. Compared with manual measurement and calculation, the method proposed in this paper is faster to measure and can greatly improve the measurement efficiency. It is notable that, there is no need to preset any parameters (e.g. the threshold). The only required operation is to input captured micrographs into the proposed algorithm, and the method can automatically recognize and measure the defects. High automaticity of the proposed method makes it user-friendly for the technicians or researchers who do not have any prior professional knowledge about CFRPs, which enhances the applicability of this method.

4.3 Robustness to the interference from the bright noise

As mentioned above, the captured defects micrographs usually appear some bright noises with similar visual features to the defects region, which may interfere the results of image processing seriously. Thus, the method robustness to the interference from the bright noise is also evaluated in this section. It can be observed from Fig. 9 that, no matter how much noise there is, all defects could be recognized and measured accurately, proving the proposed method robustness to the bright noise.

5. Conclusion

This paper proposed a digital-image-processing-based method to automatically recognize and measure the defects in the CFRPs workpiece, which is validated by drilling trails. The key findings are included as follows:

(1) A binarization algorithm based on locating the threshold on the first minima between the histogram peaks is proposed for burr area segmentation, followed by a K-means segmentation algorithm based on the number of pixels for delamination area segmentation. Two segmentation algorithms are presented to
extract defects area adaptively, which do not require adjusting thresholds and presetting any parameters. This means the proposed method has high automation and excellent applicability.

(2) The method can accurately measure burr factor with the maximum relative error of 5.76% and delamination factor with the average relative errors of 3%. Compared with manual measurement, the method would be faster (about 4 seconds per micrograph) to recognize and measure the defects.

(3) The proposed method has good robustness to the interference from the bright noise, which is the basis of recognition process.

**Declarations**

**Author contribution** Xuyan Zhang: writing-original draft preparation, methodology. Wenjian Huang: investigation, validation, reviewing and editing. Shiyu Cao: investigation, reviewing and editing. Chaoqun Wu: reviewing and editing, funding acquisition, conceptualization, supervision.

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**Availability of data and material** All data generated or analyzed during this study are included in this article and its additional files.

**Code availability** Not applicable

**Conflict of interest** The authors declare no competing interests

**References**


**Figures**

**Figure 1**

Typical micrograph of the drilled hole defects

**Figure 2**

Diagram showing the process steps for delamination and burr prediction.
Flowchart of the proposed methodology

Figure 3

(a) The basic principle of the recognition of the defects region, (b) the converted gray defects image, (c) the filtering results by using three classic filtering algorithms, (d) bimodal histogram of image after
median filtering, (e) Gaussian filtering and the result of threshold selection, (f) the segmentation result of drilled hole, (g) the extraction of the burr profile, (h) the extraction of the burr area.

Figure 4

(a) the masked micrograph, (b) 3D pixels distribution of the masked image, (c) 3D pixels distribution of the masked image after K-means segmentation, (d) the segmented image, (e) the image after filling small holes, (f) the polar coordinate system, (g) the Cartesian coordinate system, (h) the image after filtering, (i) the polar radius distribution, (j) the polar angle distribution.
noise area, (f) the image in the Cartesian coordinate system, (g) the image in the Polar coordinate system, (h) the contour scanning of the delamination, (i) a scatter plot of polar coordinates on 360 rays, (j) the connection line of max polar radius points on 360 rays, (k) the result of recognition of the delamination contour.

Figure 5

Schematic figures of defects measurement: (a) area-based burr measurement, (b) nominal hole, (c) burr-free area of the drilled hole, (d) $F_d$-based delamination measurement

Figure 6
Illustration of experimental setup: (a) NC machine tool, (b) the detailed drilling test setup, (c) the HSS twist drill geometry, (d) the CFRPs workpiece

Figure 7

The (a) schematics of the image acquisition setup, (b) captured micrograph and (c) internal view of the image acquisition setup
Figure 8

Burr factor and delamination factor comparison between the manually-measured and automatically-measured ones
### Figure 9

Method robustness to the interference from the bright noise.