Automatic defect detection in fiber-reinforced polymer matrix composites using thermographic vision data

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Abstract
The detection of internal defects, not visible to the naked eye from the outside of materials, using non-destructive testing (NDT) are increasingly requested by industrial processes. This study proposes a novel methodology for acquisition and processing of images from a thermographic camera using computer vision methods to test composite materials made of a polymer matrix reinforced with glass, carbon, and kevlar fibers. The image is acquired while cooling the sample, following a suggested procedure. The processing methodology is divided into three steps, image pre-processing, image processing, and data post-processing. In image preprocessing, filters are applied to improve image quality, and methods are proposed to segment and identify the region of interest. In image processing, a blob analysis method is suggested for defect identification, isolation and characterization. A data analysis method is proposed for the post-processing step to characterize the defects identified in the previous step. Samples with known defects in terms of size, geometry, and location were used to test the developed system. The system showed high performance, achieving 98% accuracy, and suitability for defect detection larger than 0.5 mm in thickness and 600 mm² in area. The experimental results showed that the algorithm did not detect any false positives, and that the type of reinforcement used in the analyzed samples had no influence on the results. On the other hand, the depth of the delaminations had an influence on the pixel intensity contrast of the defect region, and its instant of maximum contrast. The lesser the depth of the defects detected, the higher the value of their intensity and the shorter the instant of maximum contrast.

1. Introduction
The existence of internal defects in polymer matrix composite materials is a matter of concern, since these defects negatively impact the performance of these materials and can compromise their integrity and the safety of people. Thus, detection and characterization of these defects using non-destructive testing (NDT), such as tests based on thermal, optical, acoustic, electrical or magnetic techniques, is of high importance [1]. Hybrid thermal and optical techniques, such as active thermography that allows visualization of heat diffusion in a part, are reported as good solutions for detecting internal and external defects in polymer matrix composite materials [2, 3]. However, conventional active thermography is centered on the human worker making an inspection test time-
consuming and error-prone [4]. Automation of thermographic inspection has been little explored, being limited to the detection of surface defects in composite materials and surface and sub-surface defects in metallic parts [5]. Antonello et al. suggested for the detection of surface defects in Carbon Fiber Reinforces Polymer (CFRP) blades the use of Pulsed Phase Thermography (PPT) and an Unsharp Masking method [6]. Ghidoni et al. proposed using a laser beam, a thermographic camera, and conventional image processing methods in conjunction with support vector machine to detect surface-visible defects such as cracks in metal parts [7]. Benmoussat et al. suggested using eddy currents to indirectly heat a part and a Reed and Xiaoli Yu detector (RX) and a regularized adaptive RX to detect and locate surface and sub-surface defects, such as cracks, in metal parts [8]. No comprehensive image processing technique has yet been proposed that provides fully satisfactory results and can be used for the detection of defects with different geometries, in different materials, and in parts of different geometries.

This study proposes a novel methodology for acquisition and processing of images from a thermographic camera using computer vision methods to test composite materials made of a polymer matrix reinforced with glass, carbon, and kevlar fibers. Experimental tests were performed using the developed system to prove its effectiveness.

2. Methodology

In this study an automatic system for defect detection in composite parts using the technique of active transient thermography in reflection mode is proposed. The innovations proposed in this study are at the level of the hardware used (described in section 2.1) and at the level of the software (described in section 2.2).

2.1 Experimental Setup

The automatic visual inspection system developed consists of the following elements: a thermographic camera IRS336 series from Automation Technology; four high heat transmission halogen lamps of 175 W (positioned 70 cm from the surface of the sample, guaranteeing the sample’s thermal excitation); a DAQmx module from National Instruments and a computer (where communication is established between the thermographic camera and the data processing software used). The experimental setup is represented in Figure 1.

The system performs the test automatically through automatic heating of the sample under analysis and automatic video acquisition, according to the parameters (sample heating time and video acquisition time). The video acquisition starts just as the lamps turn on and they occur during the time specified by the user.

2.2 Defect detection algorithm

To automatically detect defects in parts, it is proposed the hardware presented in Section 2.1, to acquire thermography video frames from a part to be inspected, and an algorithm, depicted in Figure 2, to detect defects. This algorithm is divided into three steps: image preprocessing; image processing, and data postprocessing.
Figure 1. Representative scheme of the experimental setup

Figure 2. Architecture of the algorithm for part defect detection. The thermography testing step consists of image acquisition during controlled heating and cooling of the sample

2.2.1 Image pre-processing
The captured images (frames) are subsequently pre-processed (cropping the region of interest of the image captured, and simplifying and improving their quality, frame by frame), to facilitate subsequent image processing.

2.2.2 Image processing
These images are then processed through three main filters that enable the system to distinguish a defective area from a non-defective area. The first two filters applied to each frame are a combination of morphological dilation and an image arithmetic operation, with the goal of removing uneven illumination and enhancing the boundary of the detected anomalies. This process can be represented according to Equations 1 and 2.

\[
I_1_{ij}(t) = 2 \cdot I_{\text{sample}ij}(t) - A \cdot I_{\text{sample}i+m,j+n} 
\]  
\[
I_2_{ij}(t) = B \cdot I_{1, i-m,j-n} - I_{1_{ij}}(t) + 40 
\]

Where \(I_{\text{sample}ij}\) represents the pixel \((i,j)\) from frame \(t\) of the pre-processed test images, \(A\) represents the matrix that characterizes the morphological dilation factor for the first
filter. Similarly, $\mathbf{B}$ corresponds to the matrix that represents the morphological dilation factor for the second filter. $\mathbf{I}_{ij}(t), \mathbf{I}_{sij}(t) \in [0, 255]$ denote the results of the first and second filter applied, respectively. The indices $m$ and $n$ correspond to the pixel neighborhood $(i, j)$ traversed by the structural elements $\mathbf{A}$ and $\mathbf{B}$.

To bring out potential defects, the images resulting from the second filter are then segmented according to their histogram’s peak (which is used as the threshold value). From this segmentation, blobs that may or may not correspond to defects in the sample are detected. To avoid small blobs that correspond to image noise effects, a two-step noise reduction method is used. In a former step, each blob present in a frame is stored if its area is comprehended between a range of values that consider the surface area of the sample (min$A$ and max$A$). In a latter step, each blob’s position over time is examined, and those that have a stable position over time are considered. To make this distinction possible, the image matrix of the isolated sample is divided into nonoverlapping blocks of 6×6 pixels, each with its respective index. The centroid of a defect will stabilize in the same zone, which means that the coordinates of centroids that appear several times in the same block will correspond to a defect. The sum of the incidence of blobs in each block over time is then performed and stored in $\mathbf{S}_{\text{block},kl}$. When Equation 3 is validated, a block containing a defect is identified and its coordinates stored in $\mathbf{V}_{\text{index},d2}$. $\mathbf{f}_r$ represents the ratio between the number of frames representing a NDT test ($\text{frame}_{\text{final}} - \text{frame}_{\text{initial}}$) and the number of times a blob must be identified in these frames to be considered a defect. To consider coordinates that coincide with the boundary between the created divisions (blocks), the values around the indexes stored are added to the respective index value. The indexes with the new values must verify a second condition similar to Equation 3, with a new fraction ($\mathbf{f}_r$, greater than $\mathbf{f}_r$) of the analysed frames.

$$\mathbf{V}_{\text{index},d2} = \begin{cases} k, l & \mathbf{S}_{\text{block},kl} > \mathbf{f}_r \cdot (\text{frame}_{\text{final}} - \text{frame}_{\text{initial}}) \\ \emptyset & \mathbf{S}_{\text{block},kl} \leq \mathbf{f}_r \cdot (\text{frame}_{\text{final}} - \text{frame}_{\text{initial}}) \end{cases}$$ (3)

2.2.3 Data post-processing

With all the blobs correspondent to defects properly stored, the average position of the centroids ($\overline{\mathbf{P}_d}$) of each detected defect is calculated, as well as each defect’s average areas ($\overline{\mathbf{A}_d}$) in pixels and the difference between the pixel intensity of each defect detected with the average intensity of its neighborhood over time ($\mathbf{I}_{\text{contrast}}$), according to Equations 5, 6 and 7.

$$\overline{\mathbf{P}_d} = \frac{\sum_{t=\text{frame}_{\text{initial}}}^{\text{frame}_{\text{final}}} \mathbf{P}_d(t)}{\text{frame}_{\text{final}} - \text{frame}_{\text{initial}}}$$ (5)

$$\overline{\mathbf{A}_d} = \frac{\sum_{t=\text{frame}_{\text{initial}}}^{\text{frame}_{\text{final}}} \mathbf{A}_d(t)}{\text{frame}_{\text{final}} - \text{frame}_{\text{initial}}}$$ (6)

$$\mathbf{I}_{\text{contrast}}(t) = | \mathbf{I}_{\text{sample},ij}(t) - \mathbf{I}_{\text{neighbourhood},ij}(t) |$$ (7)
3. Results and Discussion

The defect recognition system was tested on defective samples produced by fused deposition modeling (FDM). The matrix of the samples was composed of thermoplastic polymer polylactide (PLA) and reinforced with Kevlar (K), carbon (C), or glass (G) fiber. The samples’ dimensions were 120×120×5.5 mm³. Inside, there were defects (delaminations) 12×50×0.5 mm³ in size, located at different depths, i.e., defect type I, II, and III were located at 1.38, 2.75, and 4.12 mm from the surface, respectively. Forty-five tests were performed to cross-reference the three different materials constituting the samples with the three types of defects. A thermographic video with the results of a test can be seen at the Video link (https://tinyurl.com/5ha99yym).

The tests were performed in a place free of people movement, under the presence of indirect natural light rather than artificial light. The parameters used for the performed tests are shown in Table 1. The image processing values were obtained empirically. Figure 3 shows the result of a test in which the two defects in a carbon fiber-reinforced composite sample were detected.

<table>
<thead>
<tr>
<th>Table 1. Parameters used for the performed tests</th>
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<td><strong>Thermography parameters</strong></td>
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<td>Sample heating time (s)</td>
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<td>Video acquisition time (s)</td>
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**Figure 3.** Composite sample: (a) with carbon fiber reinforcement (120×120×5.5 mm³ in size); (b) with two defects, highlighted by circles, depicted in a thermographic image; (c) difference between the pixel intensity of each defect relative to the average intensity of its neighborhood over time

The results obtained for each test during the instant of maximum contrast between the intensity of the pixel of the detected defects with its neighborhood are shown in Table 2.

<table>
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<th>Table 2. Results of the tests performed on all samples, with defects at different depths</th>
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<td><strong>Sample reinforcement</strong></td>
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<tr>
<td><strong>Defect type</strong></td>
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<td><strong>No. of defects detected</strong></td>
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<tr>
<td><strong>Total no. of defects</strong></td>
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<tr>
<td><strong>Max contrast</strong></td>
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<td><strong>Time of max contrast (s)</strong></td>
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<td><strong>Average defect area (mm²)</strong></td>
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The system performed well, achieving 98% accuracy by detecting 44 out of 45 defects present in the samples. Only one defect, type II, contained in a Kevlar-reinforced sample was not detected because the centroids of its respective blob over time were on the boundary between more than two divisions, not adding up all centroids and not fulfilling the imposed condition to be considered by the system. The values observed for each defect type are similar between the different sample reinforcements. The areas calculated by the algorithm are close to the actual areas of the defects (600 mm²).

4. Conclusions

The methodology suggested in this study proved to be effective for performing thermography NDT and automatic defect detection in composites. The system showed high performance, achieving 98% accuracy, and suitability for defect detection with an area of 600 mm². Most of the tests performed in the samples with type I, II and III defects were able to detect all the delaminations present in the samples. The automatic defect detection algorithm did not detect any false defects in any of the tests performed, proving to be robust and reliable. The type of reinforcement used in the samples had little influence on the results. On the other hand, the depth of the delaminations influenced the contrast of the pixel intensity in the defect region, and its instant of maximum contrast. The smaller the depth of the defects detected, the higher the intensity value and the shorter the instant of maximum contrast.

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References