Nondestructive inspection of aerospace composite laminate using thermal image processing

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Abstract

In this work, a novel image segmentation method in thermographic images using the computer vision algorithm, active contours, is presented. These studies were done on thermal images obtained from pulse thermography. Many aerospace components are made of composite laminates. De-bonds/de-laminations set in during the manufacturing or in-service stages of these materials. Identification of de-bonds in composite laminates is a difficult task and faces many challenges when it is done through the processing of thermographic images. The first challenge is to get an accurate seed point to be used in active contours. In this study, the seed points for active contours were obtained from the moving averages of the pixel values taken along the region of interest lines. It is shown that the active contours with the help of seed points identified through this method are able to distinguish the de-bonds. The experimental results, supported by segmentation metrics, suggest that the segmentation method used here outperforms some earlier results which were based on the combination of Gabor filters, watershed models and divide-and-conquer methods such as subdivision of images.

Keywords Active contours · Feature extraction · Noise removal · ROIL · Thermal imaging

1 Introduction

Aerospace structures use materials that are lightweight but possess high strength and stiffness. Composite materials are the ones used to satisfy the above requirements. The composites are made out of different materials having different physical properties, but in combination give the required properties. The composite laminates consist of various layers made of different materials stacked at different angles. Glass fiber-reinforced polymer (GFRP) and carbon fiber-reinforced polymer (CFRP) are some of the commonly used materials used in aerospace structures. The main drawback of structures made of such materials is the presence of inbuilt defects caused during their manufacturing and also during in-service operations [1]. De-lamination or de-bonding is the more frequently seen

defect, in which some layers of the laminate get displaced from the others. Detecting these defects and undertaking corrective measures is very essential while using composites. Visual inspection alone is not of much help in identifying them due to the fact that the defects can occur in between the layers. Therefore, scientific techniques, that do not cause damage to the material, are needed to identify them.

Nondestructive testing (NDT) is a testing and analysis technique to evaluate the properties of a material, component, structure or system for characteristic discontinuities or differences without causing any damage to the original material or part. These methods are based on the use of signals in different domains like X-rays, eddy currents, shearography, ultrasonics, microwaves, thermography,

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acoustics, etc. [2]. Nondestructive inspections are fundamental to the realization of aerospace structures.

In the aerospace industry, ultrasonic C-scans have been used to assess the internal quality of large components made of composites. This kind of testing enables the determination of the depth of the defects with good accuracy. On the other hand, for the effective use of ultrasonics, several inspections with different probes are needed, considerably increasing the effort, time and cost involved [3]. Infrared (IR) thermography is one method that has become popular and has the advantage of being a non-contact-type cost-effective NDT where it is possible to have a rapid scanning of the structure. Garnier et al. [4] have compared various NDT methods, including infrared thermography and ultrasonic testing. It was reported that if ultrasonic testing takes about 30 min, the infrared thermography inspection could be completed in 30 s.

A thermographic image is obtained when a thermal picture of a specimen is formed based on infrared radiation from the specimen. In pulsed thermography (PT) [5], a thermal pulse using flash lamps is applied on the structure to be inspected and an IR camera is used to measure the temporal evolution of the surface temperature. After the initial pulse, heat wave propagates under the surface by diffusion and changes rapidly. For a homogeneous material, the surface temperatures at different locations decrease uniformly during the cooling process. The presence of an internal de-bond alters the diffusion rate, and the defect location can be identified by observing the surface temperature difference [6].

Despite the popularity, there are limitations while using thermography [7]. Studies have shown that inspection by pulsed thermography is affected by non-uniform heating, emissivity variations, lateral heat diffusion and optical reflections. [6] observed that thermal images processed by the system have the problem of edge blur, low resolution and non-uniform heating. The overall signal-to-noise ratio in thermal images is relatively less, and also, the thermal resolution between the de-bonded region and non-defective region is very low. This resulted in a very low contrast difference between defective and non-defective regions. Finding the defective regions from such poor contrast images remains a great challenge in NDT.

To overcome this difficulty, image enhancement through several noise removal techniques is employed [8]. Several approaches have been developed to enhance the reliability and sensitivity of experiments [9]. As a result, NDT has progressed to an automatic defect detection technique based on thermographic signal reconstruction (TSR), analytical fitting, unsupervised machine learning and difference temperature signal. A finite impulse response (FIR) filter was designed by [3] to process input thermal signals and reduce measurement

noise. They tested the ability of the proposed FIR-aided methodology in the classification of defects on an actual sample of a CFRP laminate, filled by both surface and in-depth inclusions of foreign materials. Two test regions and a training region with 3 different classes (with surface defects, in-depth defects and a homogeneous region) were tried. Quantitatively, the improvement of image contrast can be viewed by inspecting the image entropy. Studies based on before and after application of FIR showed that the entropy of the feature maps of the training region, and two test regions showed increases of 8.62%, 4.86% and 10.88%, respectively. This clearly proved that the application of the FIR filter increases the number of details within the feature maps. Moreover, the comparison of results before and after the application of the FIR filter shows that precision values are almost equal. On the contrary, the recall value computed for surface defects class against in-depth defect class increases about 19.8%. It means surface defects are better recognized over the sample laminate. As discussed in [10], classical methods treat thermal maps as standard images. As thermal imaging follows the well-known physical laws, feature representations with physical meanings can be much more useful than standard processing.

One of the major works reported on the thermography applied to CFRP specimens is by Ibarra-Castanedo et al. [11]. In their work, 25 Teflon pieces of different sizes were embedded in the specimen at different depths. For the purpose of preprocessing, they made the image undergo correction for fixed-pattern noise, vignetting, bad pixels, and then, the thermogram was calibrated for temperature. Further noise reduction was achieved by subtraction of a cold image. The Gaussian method was used for noise smoothing. For the reduction of artifacts caused by surface geometry and non-uniform heating, differential absolute contrast (DAC) has been proved to be highly effective. It was observed that the presence of noise was a major issue in pulse phase thermography (PPT), and hence, the possibility of a combination of PPT and TSR was considered by them. A modified DAC algorithm also was developed based on the thermal quadrupoles theory to further validate DAC [12]. Lopez et al. [13] were able to produce a new set of thermal images by decomposing the original data into latent variables. This technique was based on partial least squares regression, and Feng et al. [6] proposed a combination of TSR and automatic seeded region growing (ASRG) algorithm for processing the thermographic images of CFRP. It was successful in minimizing uneven illumination and enhancing the detection rate. Five different specimens with varying material properties were tried with independent component analysis (ICA), principal component analysis (PCA), PPT and TSR which gave

an average POD (probability of detection) of 0.62, 0.7, 0.5, 0.72, respectively. The algorithm based on their method gave a better POD of 0.88.

In the recent past, several computer vision-based techniques [14] have been getting evolved in the processing of thermographic images of CFRP laminates. Image fusion followed by texture improvement using Gabor filters and applying the watershed algorithm for edge detection helped in identifying a few defects in a composite laminate [15]. Since the defect detection rate was not up to the expected level, other methods were looked upon.

Sacco et al. [16] explored machine learning/artificial intelligence methods in advanced manufacturing applications like composite manufacturing. They designed a new inspection software for the automated fiber placement (AFP) process. The AFP process brings together the fields of composite materials and precision robotic placement to generate large-scale composite structures. This ML-based vision system allowed for defect data to be fully integrated into the manufacturing process. They used many algorithms like K-nearest neighbors (KNN), support vector machine (SVM), PCA, etc., to detect several types of defects like gap, overlap, wrinkle, twist, missing tow, splice and pucker. They used fully convolutional network (FCN) principle to perform segmentation, followed by marching squares algorithm (MSA) to place a bounding polygon around the boundary of the defect pixels. They calculated the pixel accuracy for a set of approximately 50 images. Accuracy obtained for finding a non-defect area was 99%. For a gap and a twist, accuracy of more than 75% was achieved. This research aided in the repair of composite cylinders manufactured in their site. However, it is a known fact that it requires a large dataset to successfully develop workable ML/AI solutions. This restricts the exploitation of ML/AI algorithms in this field.

Kass et al. [17] introduced active contours which provided a unified treatment for a group of visual problems. Lines, edges and subjective contours could be found by the same techniques. They found that tracking these features through motion and matching them in stereo, made things much easier. In their work, several samples as varied as wood images, pear and potato images, stereogram of bent piece of paper and also a video sequence of human lip movements were investigated using active contours. Since then, active contours have been widely used in different areas such as the medical field [18–21] and urban planning [22–24] of which, studies in the medical field form the major chunk.

However, there are a few difficulties in the usage of active contours [18–21]. The first problem is the initialization of control points, which must be close to the object of interest; otherwise, convergence does not happen. The second drawback is the propensity to stagnate in local

minima giving an inaccurate convergence to the boundaries of the object. To address these shortcomings of the traditional active contour method (ACM), the univariate marginal distribution algorithm (UMDA) was adopted by [18]. Cruz-Aceves et al. [19] proposed a new image segmentation method based on multiple active contours guided by differential evolution, called MACDE. They undertook the human left ventricle segmentation on a subset of magnetic resonance (MR) images. The dataset consisted of 23 MR images of size 512×512 pixels. They did comparative studies through Dice index, Jaccard index and Hausdorff distance from among the regions outlined by the experts, classical ACM and MACDE. They suggested that MACDE was the most competitive, especially for medical image applications.

Tseng et al. [20] utilized multi-population particle swarm optimization (PSO) which can find the object efficiently and accurately with the help of a larger searching window, without an additional computation time. PSO is an optimization algorithm having origins from evolutionary computation together with the social psychology principle. It is a stochastic optimization, and it uses the concept of fitness. Also, it provides a system so that individuals in the swarm interact and share information, which is similar to the social behavior of insects and human beings. In ACM, suitable control points near the object of interest are initialized. These control points are moved iteratively. Four diverse types of images of star, pepper, computerized tomography (CT) and supersonic images were chosen for the study. Before performing ACM, each image of size 256×256 was filtered by 3×3 averaging filter to reduce the noise. For each particle swarm, the window size was chosen as 30×30 centered at the current control point of that swarm. They took a supersonic image of the womb fibroma which had serious background noises and several small pieces in an image. In the traditional method, the searching window was set as 15×15 . The executing time was 0.032 s. The proposed method by them used 15 particles for each swarm and the executing time was 0.016 s, which was faster, and also the object boundary was located more precisely. Xingfei and Jie [21] also tried to address the problem of initialization sensitivity. In their scheme, the contours were generated and initialized according to the centers of divergence which were based on gradient vector field of the image.

As seen in the literature, the de-bond detection in composite laminate based on thermographic image is still faced with issues. Though several works report on the successful application of active contours, they are seldom applied to thermal images of composite laminates for this purpose. An attempt is made in this work, to use active contours in thermographic images for detecting the de-bonds in composite laminates. Suitable parameters for

active contours are arrived at after several studies. One needs to identify the seed point before applying the active contour. Suitable processing of the pixels along region of interest lines (ROILs) is explored to identify the seed points. It is shown that the proposed methodology is able to detect the de-bonds. To develop the methodology concluded in this work, thermal images of a composite laminate having simulated defects at identified locations are taken and several investigations are carried out. Details of these investigations and the results are presented.

This paper is organized as follows: Sect. 2 describes the experimental setup used in the study including the details of the specimen. The proposed methodology is dealt with in detail in Sect. 3. Various steps in the identification of defects are explained in Sect. 4. This is followed by results and discussion in Sect. 5 and conclusions in Sect. 6.

2 Experimental setup

A sample composite laminate with induced defects at pre-determined locations was created. To validate the proposed method, the defects identified by the algorithms used here are compared with the defects created. In this section, the experimental setup used for imaging the composite laminate is presented.

A composite symmetric laminate of size 100 mm × 100 mm was considered for the experiment. The laminate consisted of 26 layers of CFRP, and the layup was symmetric. The layup of 13 layers was [0/0/+45/90/−45/−45/90/+45/0/0/+45/90/−45], and the same set of 13 layers was placed again such that the 26 layers formed a symmetric laminate. The thickness of the laminate was 2.4 mm. The specimen was made out of unidirectional epoxy resin (Hexcel M18, specific gravity 1.16, tensile strength 80 MPa, shear modulus 1.3 GPa).

To simulate the defect, a material having a very low thermal conductivity compared to the parent material was embedded. The thermal conductivity of Teflon is 0.25 W/mK and that of the specimen is 2.95 W/mK. In the present

experiment, Teflon pieces having a thickness of 0.1 mm and a size of 5 × 5 mm were embedded during the primary bonding of the laminate. The defects were embedded at 16 locations (layers 2, 4, 5, 6, 8, 10, 11, 12, 14, 16, 17, 18, 20, 22, 24, 25) which corresponded to various depths in the laminate. Though it appears to be one sample, the defects were induced at different layers to create multiple scenarios of de-bonding. We simulated multiple (16) samples in a single specimen. The details are shown in the left part of Fig. 1. The aim was to detect these artificially induced defects in the laminate.

Thermal images of the specimen were obtained through pulsed thermography, for which two flash lamps (of make Broncolor Topas A8) with a flash energy of 6100 J each were used. An infrared camera (Thermo CAM SC3000) captured the images. The image spectral range of the camera was 8–9 μm, and the thermal sensitivity was less than 20 mK at 30 °C. The image was captured with a field of view 20° × 15° and had 320 × 240 pixels.

In this experiment, the specimen was kept at a distance of 50 cm from the two flash lamps. The lamps were kept at 45° to the specimen. The flash lamps were used to generate heat pulse. Once the pulse was generated, the camera took pictures every 10 ms. Hence, we had totally 20 images from a single capture. One such image, which was taken exactly during the flash, is shown in the right part of Fig. 1.

3 Proposed method

Before processing the thermal image, one has to first perform image enhancement. In other words, one has to improve the quality of the image. In image enhancement, modification of the image is attempted such that it results in an image which is more suitable than the original image for the specific application. Since the enhancement techniques are unique to the particular problem, the word 'specific' is important in this context. Image enhancement not only improves the quality of the image, but also sharpens the image characteristics and reduces the noise factor.

Fig. 1 Specimen with defects and its thermal image

Various tasks in this are contrast adjustment, brightness, noise reduction, filtering and edge enhancement.

The image enhancement methods which we do as part of preprocessing are of two types—spatial and frequency domain methods. Spatial domain methods deal with direct manipulation of pixels in an image, whereas frequency domain methods are based on modifying the Fourier transform of an image.

Some of the basic intensity transformation functions are the image negatives, log transforms, gamma transformations and piecewise linear transformations [14]. Enhancement using image negatives is suited for enhancing white or gray detail embedded in dark regions of an image, especially when black areas are predominant. To expand the value of dark pixels while compressing the higher-level values in an image, we use log transformations. Gamma transformations map a narrow range of dark input values into a wider range of output values. Gamma correction is critical while displaying an image accurately on a computer screen. Incorrect applications can result the image look either bleached out or too dark. Piecewise linear functions have the advantage that, there are some implementations of some transformations which are practical only if formulated through them. The major disadvantage is that their specification requires considerably more user input.

Histograms are simple to calculate and form the basis for numerous spatial domain processing methods. One of the most popular methods for image enhancement is histogram equalization. Histogram equalization automatically determines a transformation function that aims to generate an output image that has a uniform histogram. It is faster and simple to implement. But there are cases when this is not the best approach. It is sometimes useful to specify the shape of the histogram that we wish. This is called histogram matching. It has to be noticed that in both histogram equalization and histogram matching, only an approximation to the desired histogram is achievable. Another method used for enhancement is adaptive histogram equalization. This method computes several histograms and uses them to redistribute the lightness values of the image. It enhances the local contrast and improves the definitions of the edges in each region of an image [25].

The various steps involved in this study are: preprocessing of the thermal image as part of image enhancement, detection of candidate defects, defect localization and segmentation, followed by an analysis of the results. The basic architecture of the proposed new method is shown in Fig. 2.

As mentioned above, we have to subject the image to preprocessing first and adaptive equalization of histograms is used on the thermal image as part of enhancement. Once this is done, the image is ready for further

processing. The next two stages are: 1. identifying the defect candidates, focusing on identifying the probable candidate defect region, and 2. defect localization, in which the false candidates are eliminated and the true defect regions are localized. Details of these stages are explained in the following sections.

4 Identification of defects

4.1 Candidate selection

In our previous work [15], as part of enhancing the image, an iterative process of dividing and subdividing the image was tried. Texture improvement was attempted using Gabor filter. However, all the defects were not detected in the process due to poor image contrast, and a new approach was needed. In this new approach, the first important step was to shortlist the probable candidates for the defects.

For selecting the seed pixel for region growing, one can use various approaches like first-order or second-order gradients or edge pixels. However, these features based on gradients were not used here because thermal images have a high degree of noise and the application of gradients for candidate pixel selection might mislead the selection process. Hence, we have used a different method in this study.

Kiadtikornthaweeyot et al. [26] used a profile of intensity values along the ROIL for image enhancements of satellite images. Jeong et al. [27] applied this methodology in maritime images. Mahmod et al. [28] studied a composite laminate panel with its ROIL of intensities through a defect area and a good area. But they have not applied it on the thermal images of composite laminates having de-bonds.

Considering the above, ROIL was used in this study. In this, the variation of the intensity is plotted along a line. The intensities along this line are referred to as ROIL values. Variation of the intensities gives information on the defect. Figure 3 shows a few imaginary lines drawn on the image under consideration, through non-defective areas.

Intensity variations along the ROIL for a few non-defective areas are shown in Fig. 4. It is clear that there are no sudden changes and the intensity varies smoothly, indicating the absence of any defect.

Now, consider four horizontal imaginary lines through the possible defect region as shown in Fig. 5.

If the intensity values are plotted along this line, the peaks and troughs seen are the possible candidates of defects. Intensity variations along one of the ROILs given in Fig. 5 are shown in Fig. 6 (top curve). Though some peaks are visible, it needs improvement.

Fig. 2 The proposed method with moving average ROIL and active contours

Fig. 3 Three ROILs through non-defective areas

4.1.1 First-order difference values

Contrast is the essence of recognizing the defect. So, in the next step, we consider the differences of two adjacent intensity values, called first-order difference values (FOD). Both the ROIL values and FOD values of the first imaginary line of Fig. 5 are plotted together for comparison in Fig. 6. In Fig. 6, the top curve represents the ROIL values and the bottom curve represents the FOD values. It is clear from the results that the image is not enhanced sufficiently to distinguish the defects, by considering the FOD values.

Fig. 4 Intensity variations along ROILs in non-defect region

Fig. 5 Four ROILs through possible defects

4.1.2 Nest moving average values

As discussed in the previous section, distinguishing peaks and troughs in noisy images was difficult even by using the FOD values. To overcome this limitation, we explored the

Fig. 6 ROIL and its first-order difference along first row

usage of nest moving average [29]. The moving average filter calculates the average of a fixed number of input signal points to produce a point in the output signal. Equation (1) mathematically represents the above calculation.

$$y[i] = \frac{1}{M} \sum_{j=0}^{M-1} x[i+j] \quad (1)$$

Here, $x[i]$ denotes the input signal, $y[i]$ denotes the output signal and M refers to the number of points which was used in the moving average. Equation (2) depicts a four-point moving average filter, at the point 80 of the output signal:

$$y[80] = \frac{x[80] + x[81] + x[82] + x[83]}{4} \quad (2)$$

Let us see the moving average of seven values of the intensities for each possible defect row (or line) as plotted in Fig. 7.

It is seen that this process has helped in getting a smoothened curve. From the left, the first two defects were detected (note the two peaks). The third defect was not visible. But the fourth one had a very good detection (the trough at the end).

Let us now examine ROIL and FOD of row 3 of Fig. 5 as shown in Fig. 8. It is difficult to identify the defects. Now, consider its moving average, shown in Fig. 9. This has yielded very good results. This moving average detected all the four defects ($d1-d4$), as seen from the clear troughs in the figure.

It is seen that all the defects in row 3 are detected. More importantly, the first defect from the left, which is invisible to the eye in the raw image, had a good detection by adopting this process.

A similar exercise was carried out along the other rows. One defect candidate in the first row and another in the fourth row were *not* detected by this method. However, all the other defects were detected.

Fig. 8 ROIL and its first-order difference along third row

4.2 Defect localization and segmentation through active contours

Once the defect candidates are identified, we had to isolate the real defects. To perform this function, we used active contours.

Many traditional segmentation methods like edge detection and region growing are constrained by the problem of high computation time for obtaining good results [30]. By using ACM, we are able to dynamically track the object deformation and the results are very good. This model evolved from the regularization paradigm which was applied to computer vision technology.

An active contour is an energy minimizing spline [31]. Active contour models are applied in multiple areas for the purpose of image segmentation. In healthcare, segmentation of images from different regions of a human body is done to diagnose and detect health conditions. Tumors,

Fig. 7 Moving average value of intensities along the ROIL of first row

Fig. 9 Moving average value of intensities along ROIL of third row

cancer cells, inflations, blood clotting, cysts and lesions can be segmented from the medical images [32].

The active contours implementation can be of two types—with expanding radius and diminishing radius. In an expanding radius-type contour, an edge map of an image is first generated [33]. An initial contour will be smaller which fits inside the map. Then, it is expanded through an iterative process that minimizes the internal and external energy which moves the active contour points. As we run the active contour through this process, the points will begin to line up with the edges of the image. After running the active contour through enough iterations, the points line up with the edges of the image. In diminishing radius type, the direction is towards the center.

As explained above, active contours are fitted to shapes in images through an iterative process. The user should suggest an initial contour, which must be close to the required shape. The contour then gets attracted to features in the image evolved from internal energy, thereby producing an attractor image. In this study, active contours have been used with shrinking radius to get a clear boundary of the defect. Seed value has to be given for each defect location. The defect candidate location obtained in the previous step is used as the seed.

Seeds generated based on ROIL complement the active contours in the process of segmentation of defects. As

mentioned, initialization sensitivity is one of the limitations faced in using active contours. It is known that the initial contour must be close to the real boundary or it may converge wrongly. The ROIL solves this problem since the active contours rely on intensity values. The next section discusses the results obtained by applying the active contours.

5 Results and discussion

5.1 Influence of various parameters

The two important parameters affecting the active contour algorithm are the threshold and the radius. The threshold is a value between 0 and 1, and the radius has to be a positive integer. Several iterations were carried out varying the threshold from 0.1 to 0.9 and for radii 5, 10, 15 and 20 units. Defect detection ability with respect to the threshold values as well as the radii is depicted in Table 1.

The highest number of defects (14 defects) was obtained with radius 5 and threshold values varying between 0.6 and 0.9. The ability to distinguish the defect through the proposed method depends on the neighborhood size. Table 2 shows the sensitivity of the proposed method with the neighborhood size, varying from 1×1

Table 1 Influence of radius and threshold on the number of defects detected

Radius	Threshold								
	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
5	0	1	2	9	12	14	14	14	14
10	0	1	5	9	12	13	13	13	13
15	0	1	5	7	4	2	0	0	0
20	0	1	5	3	1	0	0	0	0

Table 2 Influence of neighborhood on de-bond detection

Pixel neighborhood	1 × 1	3 × 3	5 × 5
Detected defects	7	13	14

through 5 × 5. Based on these results, the 5 × 5 neighborhood could detect 14 defects.

For the detection of de-bonds using the above methodology, it is seen after several iterations that a radius of 5 with a threshold of 0.6 to 0.9 and a pixel neighborhood of 5 × 5 gave the optimum results.

5.2 Results with the optimized parameters

The results with the above optimized parameters with a threshold of 0.6 are shown in Fig. 10. As mentioned, 14 defects were identified clearly. Figure 10 does not show all the defects but only shows one sample defect detected from each row. Figure 11 shows all 14 defects detected separately, superimposed on the original image. The other two defects had merged into the background with almost no variations in the contrast. Also, the proposed method detected one defect as a false alarm. The false 'detection' was due to the false peak created due to the noise in the image. As mentioned earlier, the image considered was the one which was obtained during the flash.

From all the above results, we find that the proposed method can detect most of the defects by applying the active contour technique with seed point selected based on the moving average of the pixel values of the thermographic image along ROIL.

5.3 Comparison with previous results

In our previous study [15], only 4 defects were identified with clear boundaries (shown in Fig. 12) using the Gabor filter and the watershed algorithm. A fifth detection was partial. These results were due to the low contrast of the image. In the present method, the moving average of the intensities provided better results and the defects were identifiable.

5.4 Quantitative analysis

To quantitatively assess the findings of the proposed method, we have used the metrics used in the image segmentation techniques, as our defect localization process is similar to that of segmentation. We proceeded by first constructing the confusion matrix by comparing the detected and localized defect against the ground truth. Subsequently, we derived true positive, false positive, true negative and false negative for each defect. These

were used to derive the metrics, viz. precision, recall, F-measure and intersection over union (IOU). The results of the study are shown in Table 3. Normalized values of true positive (TP), false negative (FN), false positive (FP) and true negative (TN) are given.

Overall accuracy, recall (R) and precision (P) are 0.60, 0.65 and 0.78, respectively. F1-score came to 0.68 which represents both recall and precision. Intersection over union (IOU) is 0.52. It can be seen that none of the values is below 0.50.

Defect 8, even though with moderate metrics and Defect 14 with comparatively better metrics, has been a good detection. But for the new proposed algorithm, the detection of these defects would have been very difficult. As seen, Defect 3 resulted in a clear boundary which was proved quantitatively ($P = 1$, $F1 = 0.83$, $IOU = 0.71$). Noise in thermographic images due to issues like emissivity and non-uniform heating poses more challenges which account for none of the average metrics not reaching above 80% mark. Moreover, some classifiers have a tendency to converge to a reduced area with a rounded edge in comparison with the expected ones. Marani et al. [10] have observed that this behavior could be because of lateral heat flow which can reduce the thermal contrast near the defects corners. This could also be due to further alterations of the specimen during polymerization. These possible changes could not be captured in the definition of ground truths, since they were obtained by scanning the specimen before its polymerization. This could affect both accuracy and recall to some extent. However, the new method presented in this work has helped detection in a majority of cases, which was the main objective.

It can be seen that Fig. 11 from [15] shows four good detections and a partial detection. The two defects not detected in this current study have to be compared with almost 12 non-detections in [15]. Considering the huge gap in false negatives in the two studies, in quantitative assessment, the current method is an improvement over the old method.

The metrics for the watershed model segmentation detection are given in Table 4. The 11 defects not detected have hundred percent false negatives, and they do not appear in the table. The first defect detection had a higher number of false positives as can be seen visually from the image. This method, even though had limited success in total number of detections, had zero or near to zero false positives in 4 detected cases indicating high precision value of 1.0 or very close to 1.0. But this method did not score well in detecting many defects.

Fig. 10 Detection of a selected few de-bonds among the four rows

(a) First row

(b) Second row

(c) Third row

(d) Fourth row

It is clear from the iterations that, by choosing the correct seed points based on ROIL pixel values and using active contours, better results were obtained. ROIL values

refined by moving average were helpful in avoiding the pitfalls in choosing the seed point.

Fig. 11 Detection of de-bonds using the new method—superimposed view

Fig. 12 Defects detected using the watershed method [15]

6 Conclusions

A novel method for processing the thermal image for detecting the de-bonds in composite laminates has been presented. A composite laminate simulating 16 defects that are embedded at different locations with different depths is used for the investigation. Using adaptive histogram equalization, the thermal image is first enhanced. The candidate defect regions are selected using the intensity variations along ROILs. Direct pixel values or first-order difference values along ROILs could not help in identifying the correct seed points. It is shown that the moving average values of pixels along the ROILs can reveal the points clearly as it has resulted in better contrast. Application of active contours with seed points thus selected detected 14 defects out of 16. The other two defects were not detected due to poor contrast of the image. Thus, it is shown that based on thermographic images, the defects in CFRP laminates can be identified through a defect candidate selection using ROIL followed by localization through active contours. Future studies will be dedicated to investigations for detecting de-bonds in more varied samples like honeycomb sandwich panels.

Table 3 Segmentation metrics achieved in the new method

Defect no.	Metrics								
	TP ^a	FN ^a	FP ^a	TN ^a	Accuracy	Recall	Precision	F1-measure	IOU
1	0.49	0.24	0.11	0.15	0.64	0.67	0.81	0.73	0.58
2	0.32	0.02	0.36	0.30	0.62	0.93	0.47	0.62	0.45
3	0.71	0.29	0.00	0.00	0.71	0.71	1.00	0.83	0.71
4	0.41	0.23	0.21	0.15	0.56	0.64	0.66	0.65	0.48
5	0.40	0.29	0.17	0.15	0.54	0.58	0.70	0.63	0.46
6	0.41	0.27	0.13	0.19	0.60	0.60	0.76	0.67	0.51
7	0.46	0.46	0.02	0.06	0.52	0.50	0.96	0.66	0.49
8	0.37	0.27	0.16	0.19	0.57	0.58	0.70	0.63	0.46
9	0.46	0.22	0.14	0.18	0.64	0.67	0.77	0.72	0.56
10	0.36	0.17	0.23	0.24	0.60	0.68	0.61	0.64	0.47
11	0.38	0.02	0.27	0.33	0.71	0.96	0.59	0.73	0.57
12	0.41	0.51	0.03	0.04	0.46	0.44	0.93	0.60	0.43
13	0.45	0.40	0.04	0.11	0.56	0.53	0.92	0.67	0.50
14	0.57	0.35	0.02	0.06	0.63	0.62	0.97	0.75	0.61
Average					0.60	0.65	0.78	0.68	0.52

^aNormalized values

Table 4 Segmentation metrics for image from previous watershed method [15]

Defect no.	Metrics					Accuracy	Recall	Precision	F1-measure	IOU
	TP ^a	FN ^a	FP ^a	TN ^a						
1 (1st row)	0.47	0.2	0.15	0.18		0.65	0.70	0.76	0.73	0.57
2 (1st row)	0.9	0.05	0.02	0.03		0.93	0.95	0.98	0.96	0.93
3 (1st row)	0.56	0.32	0	0.12		0.68	0.64	1.00	0.78	0.64
4 (2nd row)	0.48	0.37	0	0.15		0.63	0.56	1.00	0.72	0.56
5 (2nd row)	0.37	0.45	0	0.18		0.55	0.45	1.00	0.62	0.45
Average						0.69	0.66	0.95	0.76	0.63

^aNormalized values

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Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

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