Automated defect detection in CFRP using flash infrared thermography and deep learning method

Zongfei TONG 1,2, Saeid HEDAYATRASA 1, Liangliang CHENG 1, Shejuan XIE 2, Mathias KERSEMANS 1

1 Mechanics of Materials and Structures (UGent-MMS), Department of Materials, Textiles and Chemical Engineering (MaTCh), Ghent University, Technologiepark-Zwijnaarde 46, 9052 Zwijnaarde, Belgium
2 State Key Laboratory for Strength and Vibration of Mechanical Structures, Shaanxi Engineering Research Center of Nondestructive Testing and Structural Integrity Evaluation, Xi’an Jiaotong University, 710049 Xi’an, China

Abstract
Carbon fiber reinforced polymer (CFRP) composites have become an important material for many industry applications due to their high specific stiffness and specific strength. Inevitably, defects generated during manufacturing and/or in-service process could compromise the structural health of the CFRP components. Flash infrared thermography (IRT) is a promising NDT technique, which has already been successfully applied for the detection of various defects in a range of materials. In order to bring this technique to the next level, this study aims to accomplish automatic detection and localization of delaminations in CFRP using flash IRT experiments and deep learning-based object detection method. A virtual dataset has been generated by means of a custom developed fast numerical simulator (programmed in Fortran) of flash IRT. Then, a pre-trained object detection framework from literature, i.e. Faster-RCNN, is applied to the virtual dataset using the concept of transfer learning. A comparison with classical post-processing methodologies, e.g. thermographic signal reconstruction, and principal component thermography, is presented. Finally, a CFRP slab including twelve artificial rectangular delaminations was inspected using flash IRT and evaluated through trained Faster-RCNN.

Keywords: CFRP, Non-destructive testing, Flash infrared thermography, Numerical simulation, Object detection, Transfer learning

1. Introduction
Composite materials are manufactured by combining two (or more) materials, in view of exploiting the benefits of both, and as such to outperform classical materials. As one of the promising composite materials, carbon fiber reinforced polymer (CFRP) have become an important material for many industrial applications due to its high specific stiffness and strength. Unfortunately, defects generated during manufacturing and/or in-service process could compromise the structural health of the CFRP components. Therefore, non-destructive testing (NDT) techniques are needed to detect defects as early as possible, and as such to assure the structural safety and long-term reliability of CFRP components [1].

Although a variety of characterization and inspection techniques (optical, vibrational, ultrasound, eddy current, etcetera) have already been demonstrated, each of them has its own limited capability and applicability limitations [2]. Flash infrared thermography (IRT) is a promising NDT technique, which is capable of realizing non-contact and quasi real-time measurements over a large detection area [3]. In flash IRT, a short but intense optical flash excitation is utilized to introduce a heat flux on the surface of the inspected sample, which drives the diffusion of thermal waves in the material’s through-thickness direction. Meanwhile, the surface temperature distribution and evolution are recorded with a sensitive infrared camera. The thermal diffusivity mismatch between any potential defect and the surrounding sound region results in both a locally disturbed spatial temperature distribution and an abnormal temporal temperature evolution [4]. As such, a defect can be revealed as a disturbance on
spatial temperature distribution or as a localized anomaly in the temporal temperature evaluation profile. In order to quantitatively evaluate defects from a sequence of thermographic images, the key point is to extract proper temporal and spatial features.

In recent years, deep learning-based methods, gain a lot of attention in the fields of medicine, industry and architecture in order to extract higher level features from input images [5]. The frameworks based on convolutional neural network (CNN) show a promising potential for the accurate and automated defect detection in IRT [6]. However, the feature-rich thermographic image sequences make it challenging to extract temporal and spatial features simultaneously. Many scholars consider the thermographic sequences as the array of temperature series and use full connected NN [7], RNN[8], 1D CNN[9], AE[10] to extract the temporal features of temperature series. The novel framework based on Generative Adversarial Networks (GAN) has been proposed to extract the spatial features from several frames [11]. In order to extract temporal features and spatial features at the same time, three different strategies have been proposed. Ref. [12] assumes that the temporal and spatial features are not related, the temporal features and spatial features are extracted through full connected NN and object detection architectures, respectively. In contrast to ref. [12], the temporal features are compressed in ref. [13] by PCA to enhance the detection capacity of Faster-RCNN. Finally, a hybrid of spatial and temporal deep learning architecture is proposed, which adopts segmentation frameworks and long short term memory (LSTM) network to extract spatial features and temporal features, respectively [14]. From the references mentioned above, the temporal features of thermographic image sequences not only can be used to estimate defect depth, but also to evaluate defect shapes and size, while the spatial features can only be adopted to estimate defect shapes and size. One of the common challenges is that a completely sufficient experimental training dataset is difficult to achieve in practice.

In this study, the numerical dataset was constructed using a fast numerical simulator. A traditional thermographic image processing method will be utilized as the pre-processing procedure for deep learning method. Among the traditional image processing methods, the principal component thermography (PCT), thermographic signal reconstruction (TSR), pulsed phase thermography (PPT) and the derivatives of these methods are effective strategies to highly compress the 3D data without losing too much information. By applying deep learning-based object detection methods, the automatic detection and localization of delaminations in CFRP can be accomplished.

The first challenge is to train the object detection framework by using a large and diverse set of IRT data. Setting up a complete experimental training database is difficult to achieve in practice. Therefore, a virtual database has been generated by means of a custom developed fast numerical simulator (programmed in Fortran) of flash IRT. The discontinued nodes method was utilized to simulate delamination-like defects in CFRP. Then, the PCT and TSR were exploited to construct the thermographic image dataset for deep learning-based object detection framework. Finally, a pre-trained object detection framework from literature, namely Faster-RCNN [15], was applied to the virtual database using the concept of transfer learning [12]. The structure of the paper is as follows: Section 2 introduces the developed fast numerical simulator. Section 3 presents the performance of Faster-RCNN on different simulated thermographic datasets and one experimental result. The conclusions are reported in section 4.

2. Fast numerical simulator for flash IRT applied on CFRP
2.1 Basic formulation

The process involving the flash IRT applied to CFRP is a heating conduction issue [6]. Considering
the energy conservation and Fourier heat conduction processes, the governing equation of the heat
conduction can be expressed as,

\[ \rho c \frac{\partial T}{\partial t} = \nabla \cdot (\kappa \nabla T) + Q, \quad \text{in } \Omega \]  

(1)

where \( T \) [K], \( \rho \) [kg/m\(^3\)], and \( c \) [J/(kg·K)] are the temperature, the density, and the specific heat, respec-
tively. \( \kappa \) denotes the thermal conductivity matrix of anisotropic media. \( Q \) denotes the heat generation
function per unit volume. \( \Omega \) represents the domain which needs to be solved.

The sample surface is subjected to thermal flux, which is stimulated by the excitation source of flash
IRT. The thermal flux applied on sample surface can be expressed as,

\[ -k \frac{\partial T}{\partial n} = q_{\text{flux}} \quad \text{on } \Gamma_1 \]  

(2)

where the \( q_{\text{flux}} \) [W/m\(^2\)] denotes heat flux density in the outer normal direction on the boundary \( \Gamma_1 \).

In this case, the convection boundary condition, i.e., Robin boundary condition, is considered. The
convection boundary condition can be presented as,

\[ -k \frac{\partial T}{\partial n} = h(T - T_f) \quad \text{on } \Gamma_2 \]  

(3)

where \( h \) [W/(m\(^2\)·K)] indicates convection heat transfer coefficient, \( T_f \) represents the temperature of
the surrounding fluid, \( T \) is the temperature of the solid which needs to be calculated, \( \Gamma_2 \) denotes the
boundary at which the Robin condition applies.

In the finite element technique, the continuous variable \( T \) is approximated by \( \tilde{T} \) in terms of its nodal
values through ‘shape functions’.

\[ \tilde{T} = [N]\{T\} \]  

(4)

Using Galerkin’s method, Eq. (1) can be discretized and expressed in matrix form as,

\[ [K]\{T\} + [C]\left\{ \frac{\partial T}{\partial t} \right\} = \{F\} \]  

(5)

where the stiffness matrix \( [K] \), damping matrix \( [C] \), and load vector \( \{F\} \) can be presented as,

\[ [K] = \sum_{\Omega} \left( \int_{\Omega} \nabla \{N_i\}^T \kappa (\nabla \{N_i\}) \, dv + h \int_{\Gamma_2} \{N_i\}^T \{N_i\} \, ds \right) \]  

(6)

\[ [C] = \sum_{\Omega} \rho c \int_{\Omega} \{N_i\}^T \{N_i\} \, dv \]  

(7)

\[ \{F\} = \sum_{\Omega} \left( \int_{\Omega} h \int_{\Gamma_2} \{N_i\}^T T_f \, ds - \int_{\Gamma_1} \{N_i\}^T q_{\text{flux}} \, ds \right) \]  

(8)

Equation (5) can be solved using Crank-Nicholson strategy, finally leads to,
The solution of Eq. (14) is the degree of freedom $T(t)$ at a certain time $t$.

In order to efficiently simulate delamination in CFRP, the discontinued nodes (DN) method was introduced in this study, which is represented in Fig. 1. The thickness of delamination is assumed to be zero in DN method. In comparison to simulate delamination using volume element, the DN method reduces the amount of element numbers considerably, and as such accelerates the process of constructing a virtual database.

\[
\left( [K] + \frac{2[C]}{\Delta t} \right) \{T(t)\} = \{F(t) + F(t - \Delta t)\} + \left( \frac{2[C]}{\Delta t} - [K] \right) \{T(t - \Delta t)\}
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Table 1 Parameters of numerical model

<table>
<thead>
<tr>
<th>Quantity</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Density $\rho$ [kg/m$^3$]</td>
<td>1530</td>
</tr>
<tr>
<td>Specific heat $c$ [kJ/(kg·K)]</td>
<td>917</td>
</tr>
<tr>
<td>Thermal conductivity $k$ [W/m·K]</td>
<td>$K_x = 2.71$, $K_y = 0.61$, $K_z = 0.53$</td>
</tr>
<tr>
<td>Side length of the delamination with rectangle shape [mm]</td>
<td>1.0 ~ 50.0</td>
</tr>
<tr>
<td>Depth of the delamination [mm]</td>
<td>0.23 ~ 1.61</td>
</tr>
<tr>
<td>The number of numerical cases</td>
<td>2975</td>
</tr>
<tr>
<td>Simulation time</td>
<td>$\approx 4$ min $\times$ 2975 cases $\approx 198.3$ hours</td>
</tr>
</tbody>
</table>

3. The performance of Faster-RCNN on synthetic datasets

3.1 Thermographic image datasets for Faster-RCNN

The entire time history of raw thermographic images obtained from simulation cannot be efficiently embedded into Faster-RCNN framework directly, and any individual time frame cannot represent all the features of 3D thermographic image sequences. Consequently, the PCA and TSR pre-processing methods are utilized to compress the temporal features of the thermographic image sequences. The temperature evolution of each pixel is standardized before conducting PCA and TSR, in order to remediate the effects of non-uniform heating [4]. The first four components of PCA are retained, considering that these amount for more than 95% of the variance in the original dataset. Similarly, the first four components of TSR are also adopted, while an eighth-degree polynomial is used to fit the temperature evolution profile. In order to consider the negative factors introduced by experimental errors to the datasets, the original image sequences are degraded with white Gaussian noise with a standard deviation 15 mK. Finally, four virtual databases are constructed: (1) PCA database, (2) PCA database with 15 mK noise, (3) TSR database and (4) TSR database with 15 mK noise. Each database consists of 11,900 images, of which 90% are used for training the Faster-RCNN, and 10% are used for testing. As an example, the processing results of a delamination with 10.0 mm $\times$ 10.0 mm and 1.61 mm depth are presented in Fig. 3.
3.2 The performance of Faster-RCNN

Faster-RCNN is one of the most popular deep learning-based object detection algorithms [15], and has been employed to extract spatial features from thermographic image dataset in this study. Compared with other object detection frameworks, the superiority of Faster-RCNN is that it introduces a Region Proposal Network (RPN), which embeds region proposal directly in the architecture, and alleviates the need for a selective search algorithm. A pre-trained Faster-RCNN trained on COCO dataset [18] was fine-tuned through transfer learning. The base network of the Faster-RCNN is Resnet-101, which is used for classification task [19]. The anchor’s scale ranges from 0.25 to 2.0, while aspect ratios of each anchor range from 0.1 to 10.0. The stochastic gradient descent (SGD) with a momentum term set to 0.9 was used in Faster-RCNN, whose initial learning rate is set at 0.0003. The training steps are 50000 and the batch size is set to 1. The training process and validation process (every 500 steps) cost about 6 hours on a RTX 2060 graphics card. The intersection over union (IoU) and mean average precision (mAP) [15] are adopted to evaluate the performance of Faster-RCNN in this study. The evaluation results are listed in table 2. The mAP of Faster-RCNN in validation dataset have promising
accuracy. The noise added to dataset has limited effect on the TSR results but decreases the inference accuracy of PCA results significantly.

Finally, a CFRP slab including twelve artificial rectangular delaminations was inspected using flash IRT [16]. The first TSR coefficient image was adopted to test the Faster-RCNN model trained on ‘TSR + 15 mK noise’ dataset (see table 2). From Fig. 4, it is clear that six of the defects are successfully detected. However, it can be seen that the results are heavily disturbed by the measurement noise and non-uniform background. Moreover, the defected areas are not necessarily rectangular and their thermal signature is significantly distorted. Therefore, the diversity of the training dataset (in terms of e.g., shape and orientation of defects) should be further improved for reliable detection of the irregular and hardly detectable defects.

### Table 2 Performances of Faster-RCNN for different dataset after 50000 training steps

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Loss</th>
<th><a href="mailto:mAP@.50IoU">mAP@.50IoU</a></th>
<th><a href="mailto:mAP@.75IoU">mAP@.75IoU</a></th>
<th>Average mAP</th>
</tr>
</thead>
<tbody>
<tr>
<td>PCA</td>
<td>0.00344</td>
<td>98.90%</td>
<td>93.89%</td>
<td>91.33%</td>
</tr>
<tr>
<td>PCA + 15 mK noise</td>
<td>0.00491</td>
<td>93.30%</td>
<td>85.60%</td>
<td>84.32%</td>
</tr>
<tr>
<td>TSR</td>
<td>0.04085</td>
<td>97.97%</td>
<td>93.87%</td>
<td>91.12%</td>
</tr>
<tr>
<td>TSR + 15 mK noise</td>
<td>0.01196</td>
<td>97.97%</td>
<td>95.01%</td>
<td>92.54%</td>
</tr>
</tbody>
</table>

![Figure 4 The inference result on the first TSR coefficient of experimental result](image)

### 4. Conclusions
Deep learning-based object detection algorithm (Faster-RCNN) has been applied on pre-processed simulated thermographic data, in view of automated detection and sizing of delamination defects in CFRP laminates. The numerical dataset has been obtained using a custom-built fast simulator programmed in Fortran. The PCA and TSR processing methods were used to compress the temporal features of the 3D thermographic sequences, after which, the Faster-RCNN was employed to detect and size delamination defects. Although the noise decreases the inference accuracy of Faster-RCNN trained on PCA dataset, the PCA and TSR pre-processing methods are effective methods to compress temporal features of 3D thermographic sequences for deep learning-based architectures. Experimental examination of the trained algorithm reveals the significant impact of measurement noise and non-uniform background on detection quality and shows that the defects with irregular thermal signature cannot be detected. Hence, in the future, the numerical dataset will be enriched with a wide range of defect shapes and the methodology will be demonstrated on a sparse experimental dataset by considering a second transfer learning step on this object detection framework.

Acknowledgements
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References
18. https://github.com/tensorflow/models/blob/master/research/object_detection/g3doc/tf1_detection_zoo.md