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Robust Quantitative Depth Estimation on CFRP samples using active thermography inspection & numerical simulation updating

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Abstract

A quantitative evaluation of delaminations in composite laminates encounters multiple difficulties due to the anisotropic behaviour of the laminate. Extensive calibrations for each structure are required and each depth needs certain manual modifications for optimal performance of the estimation routines. In this manuscript, a robust technique is developed using a numerical model to estimate the thermal diffusivity through the anisotropic material which improves defect depth estimation between each layer. Three different calibration depths are necessary to compute the diffusivity through a certain stacking sequence of a multi-layered composite laminate. The results are compared with the state-of-the-arts experimental evaluation techniques and with a regular numerical model. It is seen that especially for deeper defects, the optimised numerical model delivers more accurate results due to the considered anisotropic diffusivity.

Keywords: Depth Estimation, FE updating, Inverse problem, Pulsed thermography, Quantitative Non-destructive Evaluation

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1. Introduction

A quantitative accurate evaluation of defect size and depth is of crucial importance for post-production inspection and maintenance of carbon fibre reinforced polymer (CFRP) components. Especially in industries where each part should be inspected, as in the aerospace industry, the inspections are time consuming and every small improvement is useful. Most known and inspected defects in CFRP are delaminations, material inhomogeneities and cracks [1]. These defects are represented in academic test cases using teflon inserts or flat bottom hole plates [2, 3, 4]. The estimation of the depth and size is highly related to the local diffusivity around the defect. The estimation is difficult to make without preliminary knowledge of the structure lay-up and material properties [5, 6]. Therefore, it is mostly essential to perform multiple measurements at different frame rates and use extensive post-processing and calibration for each kind of structure independently [5]. For multi-layered laminates, the diffusivity measured at the surface will vary in function of the presence of a subsurface defect, its depth and the lay-up stacking [5, 7]. Therefore, in state-of-the-art techniques, a calibration procedure needs to be implemented for the dedicated case, which is time consuming and a high level of experience to successfully perform quantitative inspections is needed [5].

Numerical simulations are widely used to predict complex material behaviour of anisotropic composite materials in structural dynamics and strength analysis [8, 9, 10]. Related to those fields, Finite Element (FE) modelling can also be used to predict the axial dependencies of the anisotropic thermal diffusivity parameters [11, 12, 13]. As the modelling of an accurate CFRP model requires considerable computer effort for multi layer laminates, as shown by Steenackers et al. in [14, 11], it is necessary to develop an equivalent, simplified model for the structure containing the different fibre directions for each layer and the resulting anisotropic material properties. This equivalent model needs verification with experimental measurements and is time consuming and vulnerable to uncertainties due to the modelling simplifications as well [11]. Recent trends of other NDE inspection

techniques use advanced optimisation routines to improve experimental inspection accuracy, for example the work of De Angelis et al. [15] in shearography, the work of Darabi et al. & Lopez et al. to improve active thermography [16, 17] and the well-known FE model updating in structural dynamics [18]. Recent developments in FE model updating make it possible to implement this technique to update the equivalent FE model to the actual material properties of the inspected structure to determine the diffusivity efficiently for each defect depth and size and calculate the lateral diffusivity losses [19].

In this contribution, we will first develop an equivalent CFRP model to use the FE updating routine for thermal problems as initiated in [19]. Due to the large computational time required by the CFRP model, it is essential to use a genetic algorithm engine for best performance of the updating routine, as explained in [20]. Second, the diffusivity characteristics will be estimated through the material lay-up using the FE updating routine and the developed equivalent FE model. Finally, the developed model and diffusivity characteristic will be used to predict the defects depths inside different CFRP samples using a limited set of experimental data for each CFRP lay-up.

2. Materials & Methods

2.1. Experimental configuration & validation measurements

Pulsed thermography is performed to obtain a target set as required for the optimization routine. The technique belongs to the group of active thermography methods employing external excitation sources to provoke a heat flux within the material [17]. The system used in this study consists of two photographic Balcar FX60 flash lamps, each giving 6.4 kJ for 15 ms to produce a high-power short pulse used to stimulate the specimen surface. The acquisition of thermal images is carried out with an FPA midwave infrared camera (FLIR Phoenix, InSb, 35 μm , 640×512 pixels) and synchronised with the heat source using a dedicated synchronisation unit. A 3D matrix with the calibrated temperature transformation is built out of the measurement data. The spatial x- and y-coordinates correspond to the pixel numbers in the I and J directions, whilst the z-coordinate represents time. The

55 acquisition frequency (f_s) used was 55 Hz ($\Delta t = 1/f_s = 0,01818$ s per image), which is
 56 the maximum full-frame-rate achievable for long measurements (640×512 pixel array).
 57 Furthermore, a total of $N = 992$ frames were collected during the cooling regime, delivering
 58 an acquisition window of 18 s and after Pulsed Phase Thermography (PPT) post-processing
 59 a frequency sample rate of minimum 0.055Hz which is sufficient to accurately estimate the
 60 shallowest defect at 0.2mm depth. The measurements are performed on a CFRP006 sample,
 61 widely described in literature [17, 5] and shown in Figure 1. It consists of a 10-ply CFRP
 62 laminate with 25 Tefflon square inserts located at different depths ($0,2 \leq z \leq 1,0$ mm) and
 63 with different lateral sizes ($3 \leq D \leq 15$ mm). The optimisation results are verified using the
 64 IRview toolbox as developed by Klein et al. in [21].

Figure 1: CFRP sample, inserts location, schematical drawing.

65 2.2. Numerical model

66 The numerical simulation is performed using the COMSOL Multiphysics 5.2 software.
 67 The software uses a constant Newtonian non-linear method with a modernised implementa-
 68 tion of the DAE solver. This solver is based on the backwards differentiation formulas [22].

Furthermore, linear Lagrange elements are used to simulate the behaviour of the structure on an imposed thermal non-equilibrium starting from the surface, which represents the flash heat excitation and the emitted response of the surface due to the thermal diffusion of the signal [23]. The model consists of a stacking of different layers for each CFRP ply with thermal anisotropic properties dependent on the fibre orientation of the ply. Each ply is considered to consist of uniform carbon fibres with only one longitudinal conductivity and one different transversal in plane conductivity. Between each ply, a thin epoxy layer is modelled to simulate the practical, not ideal contact layer between each carbon ply with the third variable conductivity coefficient, perpendicular to the plies.

2.3. Diffusivity optimisation

Initially, the numerical model is calibrated for the different CFRP plies both to update the material parameters and to calculate the diffusivity from the surface until the defect depth to certain depths through the laminate by considering the lateral diffusion through each ply.

The considered optimisation routine makes use of adaptive response surface regression both to use a limited initial amount of FE models and to feed the optimisation routine which is specifically designed for thermal problems. The algorithm uses a pan and zoom function to move through the design space and delivers faster predictions with fewer iterations than standard updating routines [19, 24].

The input parameters of the optimisation routine are the different thermal conductivities ($W/m \cdot K$): $k_{f,long}$, $k_{f,trans}$ and k_{eps} , respectively, i.e. the longitudinal conductivity of the fibre, the transversal conductivity of the fibre within the ply and the transversal conductivity of the epoxy. These conductivities are further combined to the longitudinal and transversal thermal conductivities within the unidirectional plies, respectively k_{long} and k_{trans} . The fibre volume fraction which is provided by the manufacturer as 0.69 and a pressurised autoclave curing of the prepreg plies is used during manufacturing. The longitudinal ply conductivity (Eq. 1) is based on the linear mixing law theory and the transversal ply conductivity (Eq. 2) is based on the elastic moduli analogy as referred to by Pilling et al.

[25]. Due to the directional behaviour of the plies [26], the global conductivity is described in a Cartesian reference frame on which the fibres in the top ply follows the X axis (0°) and 90 degrees rotated (k_{90°) for the consecutive layer. The global conductivity properties of the plies are found using Eqs. 3 and 4.

$$k_{long} = v \cdot k_{f,long} + (1 - v) \cdot k_{eps} \quad (1)$$

$$k_{trans} = \frac{k_{eps}(k_{eps} + k_{f,trans} - k_{eps} \cdot v + k_{f,trans} \cdot v)}{k_{eps} + k_{eps} \cdot v + k_{f,trans} - k_{f,trans} \cdot v} \quad (2)$$

$$k_{0^\circ} = \begin{bmatrix} k_{long} & 0 & 0 \\ 0 & k_{trans} & 0 \\ 0 & 0 & k_{trans} \end{bmatrix} \quad (3)$$

$$k_{90^\circ} = \begin{bmatrix} k_{trans} & 0 & 0 \\ 0 & k_{long} & 0 \\ 0 & 0 & k_{trans} \end{bmatrix} \quad (4)$$

The specific heat C_p and density ρ are considered isotropic. In this way, the cumulative diffusivity $\alpha_i (m^2/s)$ from the surface to the current ply i is represented by Eq. 5.

$$\alpha_i = diag \left\{ \sum_i^n (2i - 1) \cdot (k_{0^\circ} / C_p \rho) + 2i \cdot (k_{90^\circ} / C_p \rho) \right\} \quad (5)$$

The cumulative diffusivity is approximated considering the lateral diffusivity by the FE updating routine from the experimental measurements using the physical boundaries for each parameter as presented in Table 1.

Additionally, to the defect depth of the calibration spots, the objective function calculates the integral of the absolute values of the difference between the phase signal ϕ of the defective area with respect to the sound area, as shown in Eq. 6. This additional convergence criteria avoids multiple artificial solutions and local minima as discussed in [19].

$$\varepsilon = \int \|\Delta\phi\| = \int \|\phi_{def} - \phi_{sound}\| \quad (6)$$

Table 1: Dependent optimization parameters with their boundary conditions [23, 27, 28].

Parameter	Lower boundary	upper boundary
Conductivity $k_{f,long}(W/m \cdot K)$	6.0	8.0e1
Conductivity $k_{f,trans}(W/m \cdot K)$	1.0	6.6
Conductivity $k_{eps}(W/m \cdot K)$	1.7e-1	7.9e-1
Conductivity $k_{teflon}(W/m \cdot K)$	2.42e-1	2.61e-1
Specific heat capacity CFRP $C_p[J/(Kg.K)]$	9.02e2	1.04e3
Density CFRP $\rho[kg/m^3]$	1.55e3	1.58e3
Heat transfer coefficient $W/(m^2.K)$	5	30
Emissivity	0.80	0.95

2.4. Estimation of defect depth

The defect estimation stage starts from the optimisation routine as described in section 2.3. The defect depths are next calculated using the new received conductivity parameters for all defect depths. The depth estimation routine is adapted to automatically calculate an optimal reduced sample frequency, as discussed in [5], before performing the PPT analysis on the numerical data. The depth is found using the known diffusion length μ as widely validated [29, 30, 31, 5] which can be estimated from Eq. 7.

$$z = C_1 \sqrt{\frac{\alpha}{\pi \cdot f_b}} = C_1 \cdot \mu \quad (7)$$

Where f_b is the blind frequency and C_1 the correlation constant which is typically equal to 1.82 as presented by [31]. The blind frequency is defined as the frequency on which the phase of the defective area and a sound area converges.

The results of the optimised FE model are compared with the technologies developed by Ibarra-Castanedo et al. [5] from the experimental specimen itself and with the initial numerical model used before the optimisation routine is started and which contains the standard material properties of the Comsol material database.

3. Discussion & Results

In the following section an overview of the achieved results is given. At first, the approximation of the diffusivity is discussed and compared with technical data sheet values and experimental measurements. Secondly, the accuracy of the depth estimation of the optimised model is validated using the numerical simulation and the experimental results.

3.1. Diffusivity optimisation results

The diffusivity estimation is performed with three input parameters: $k_{f,trans}$, $k_{f,long}$ and k_{epoxy} to determine the contributions of the diffusivity along each axis for the full CFRP lay-up. The response is measured as explained in section 2.3, as the estimation of the known defect depth due to the blind frequency and by comparing the sum of the phase difference for each inspected defect. An overview of the known parameters and the estimated values can be found in Table 2. The obtained conductivity parameters are shown in Table 3 and are all within their boundary limits. The optimisation routine was stopped at a global error sum for all six parameters equal to $2.5e-3$ to improve accuracy. A graphical representation of the convergence is shown in Figure 2. As can be seen, the convergence strongly fluctuates between high and low error values due to the complex parameter set. The optimisation performed 109 iterations and made use of 15 initial points all over the optimisation range. The optimisation time to find the global optimum with this high accuracy took 75 746 seconds, which is around 21 hours of computation time on a desktop computer with 6 core 3.20 GHz i7 processors and 32GB RAM. The optimisation code is adjusted for accuracy and not for optimisation time at the moment. It is shown that the used algorithm is capable of differentiating the different thermal conductivity parameters by using the model. These different conductivity parameters can be further used to improve the estimation of unknown defect depths between different layers and of other measurements performed on the same material.

Table 2: Comparison between target depths and estimated depth using the diffusivities as optimisation parameters.

Parameter	Target	Optim Result
Defect 1 depth (mm)	0.202	0.193
Defect 2 depth (mm)	0.605	0.591
Defect 3 depth (mm)	0.804	0.765
Error sum	/	2.5e-3
Iterations	/	109
Time (sec)	/	75 746

Table 3: Result optimised conductivity parameters with their boundary conditions [23, 28].

Parameter	Lower boundary	Estimated value	upper boundary
Conductivity $k_{f, long}(W/m \cdot K)$	6.0	1.43e+1	8.0e1
Conductivity $k_{f, trans}(W/m \cdot K)$	1.0	1.17	6.6
Conductivity $k_{eps}(W/m \cdot K)$	1.7e-1	6.28e-1	7.9e-1
Conductivity $k_{teflon}(W/m \cdot K)$	2.42e-1	2.53e-1	2.61e-1

Figure 2: Error convergence through optimisation process.

Figure 3: Depth estimation of the measurement data, the initial numerical model and the optimised numerical model.

Table 4: Comparison between target depths and estimated depth using the diffusivities as optimisation parameters.

Parameter	Target	Optim Result	Experimental	initial FE model
Defect 1 depth (mm)	0.200	0.193	0.202	0.198
Defect 2 depth (mm)	0.403	0.387	0.511	0.250
Defect 3 depth (mm)	0.605	0.591	0.642	0.267
Defect 4 depth (mm)	0.804	0.765	0.700	0.359
Defect 5 depth (mm)	1.01	0.958	0.702	0.495

3.2. Validation estimated defect depths for multiple defects

The obtained conductivity properties are implemented in a new FE model of the structure to estimate the defect depth on the same test sample but with different defects and more variable depths. The estimation makes use of PPT analysis as explained in section 2.4 and is validated by comparing with the experimental results and a regular, not updated FE model. The validation experimental results are calculated according to [5] with for each defect the optimal sample frequency. The calculated diffusivity parameter is remained fixed according to literature for all defect depths. Next to the experimental validation, Table 4 compares the optimised numerical model with the same numerical model but with standard material properties of the material database, as the initial starting point of the optimisation routine. A graphical representation of all results is shown in Figure 3. The reader can see that the standard numerical model delivers similar results as the experimental measurements for the shallowest defect but it has the worst accuracy for deeper defects due to the approximation of all parameters. Using the information out of the experimental measurement, included in the FE updating routine, it is possible to adapt the numerical model to estimate the depth more accurately, even from defects which were not used in the optimisation routine.

4. Conclusions

We introduced an equivalent numerical model for estimating defect depths using active thermography which functions properly for shallow defects with standard material properties.

Next the developed numerical model is used within a FE model updating routine specifically designed to estimate the thermal diffusivity through the full test sample. The results of this improved numerical model are verified using experimental PPT measurements for multiple defect depths. It is seen that especially for defects deeper than 2 plies, the optimised numerical model delivers a better accuracy than both the standard numerical model and the experimental measurements. A major advantage is that there is no need to manually adjust the sample frequency or the diffusivity for different depths. Drawback of the method is the large computation time due to the implementation of the numerical model. Therefore, we can conclude that the methodology delivers major advantages for future research and it can potentially provide assistance for inspectors to more accurately estimate deep defect depths.

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