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Model based characterisation of delamination by means of thermographic inspection

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Abstract. The objective of the work presented in this paper is to propose a fast and accurate approach for the characterisation of the delamination in single-layer metallic planar pieces using infrared thermography. This approach is based on a combination of pre-processing techniques and inversion. The inversion has been done in a reduced parameter space since the pre-processing phase gives us information about the location and the shape of the flaws in the transverse plane. The estimation of the flaws' parameters has been carried out by an iterative data fitting method involving a fast semi-analytical three-dimensional model. The robustness of the proposed approach is numerically assessed in presence of synthetic noisy data sets in different configurations.

1. Introduction

Non-destructive evaluation (NDE) techniques can be evaluated in terms of their capability to answer to two main questions: (i) detection and (ii) identification or characterisation of defects. The first question requires a qualitative answer of a binary nature. The second one refers to quantitative parameters, that is, once a defect is detected it has to be identified in terms of its parameters as size, location, nature, independently of the technique employed. This work particularly emphasizes the identification problem in thermal non-destructive testing (TNDT).

Active thermography [1] uses a thermal source in order to deposit heat in the target material creating a transient heat flow and, when finding defects, thermal contrast. The most common form of active thermography for material evaluation consists in using sources as flash lamps or lasers where a pulse of light instantaneously heats a surface and the resulting temperature is observed with a thermal camera. This technique is also known as pulsed thermography and has been extensively used as inspection technology for composite and layered structures. The detection can be on the same side as the heat source or on the opposite side, depending on the type of access to the sample. However, analysis and inversion of thermographic data tends to be challenging since the underlying heat conduction phenomenon is a diffusion process. As heat diffuses in time and space, temperature differences blur, the heat source becomes harder and harder to resolve and the contrast created by the flaws is lower.

Typical TNDT procedure results in a sequence of infrared (IR) images, obtained via an IR camera, that reflects the evolution of temperature in time. Mathematically, such a sequence can be regarded as a three-dimensional table of temperature values, with the dimensions being



space and time, $\mathbf{T}_{x,y,t}$. This recorded thermal response usually is degraded because of several factors. Uneven heating, variations of emissivity on the observed surface, optical distortions and noises of multiple nature significantly decrease the quality of the obtained thermal images. These factors limit the potential sensitivity of any method. Usually, the recorded signals are a subject of some signal processing like subtraction of the camera response when the piece under test is removed.

Several data processing techniques for reducing the amount of noise in thermal images and local storage requirements while improving the visibility of discontinuities have been proposed in the literature. These algorithms are either one-dimensional, being applied to pixel-based temperature evolutions in time, or two-dimensional, being applied to single images. Single IR images are normally filtered or segmented to reduce random noise or to analyse geometrical features of the areas of interest.

Much more information about defect parameters can be obtained by analysing the evolution of temperature in time. Therefore, most TNDT processing algorithms use pixel-based functions, which rely on one-dimensional diffusion models [2]. These models serve very well their purpose when one is trying to identify one defect at the time or defects located at a reasonable distance since the presence of one does not affect the temperature profile of the other. When the defects are located close to each other the usage of pixel-based functions, *i.e.* one dimensional models, fails to characterise those defects with an acceptable accuracy.

The usage of one dimensional models is not restricted only by the relative location of the defects but also by the depth of the defects. In situations where the defects are deeply buried in the material, or the material is too thick, the need of using a three-dimensional approach which will take into account the interaction between the defects and the occurred diffusion is of a significant importance. Yet, one cannot define a strict rule which will imply the limits of the one-dimensional model with respect to the mentioned parameters. The application of two or three-dimensional models in iterative inversion schemes is limited because of their excessive computational time since most of them are based on a numerical approaches [3].

In this work we propose a combination of pre-processing techniques and inversion to achieve an accurate characterisation of delamination-type flaws in metallic plates. We regularize the inverse problem by pre-processing the data, which brings information about the location and the shape of the flaws in the transverse plane. Thus, we are dealing with an easier problem since the size of the parameters is significantly reduced. Here we present the inversion problem by assuming that the pre-processing has been carried out, which will be presented in a future contribution. We use a fast, three-dimensional, semi-analytical direct model which is able to produce reliable data in cases of planar double-layered materials with embedded, rectangularly shaped in the transverse plane defects [4]. This semi-analytical direct model is based on an approach referred in the literature as the truncated region eigenfunction expansion (TREE) which has been successfully applied also in electromagnetics for the solution of magnetostatic and low-frequency (eddy-current) problems [5].

2. Methodology

A valuable answer to the characterisation problem can be given if one has at its disposal three essential elements: *(i)* a characterisation of the defect parameters in terms of the active parameters in the physical process used by the NDE technique, *(ii)* a direct model giving the expression of the measured quantity as a function of the active parameters of the defect and *(iii)* an inversion (or parameter estimation) technique that gives these parameters as a function of the measured physical quantities. In our case, the defect parameters are the physical parameters of the defect such as its location, its size and its thermal properties. The measured quantity is the temperature recorded as a time series at the surfaces of the sample. The theoretical value of the surface temperature \mathbf{T}_{surf} will be provided by the aforementioned semi-analytical model

where the thermal characteristics of the sample are known.

In literature one can find different parameter estimation techniques depending on the nature of the parameters one is looking for. The depth profile reconstruction, the inverse problem, consists of set of attempts for fitting \mathbf{T}_{surf} by trying all reasonable profiles. In the spatial domain the inverse scattering technique has been used to reconstruct both thermal conductivity and heat capacity depth profiles [6] and the conjugate gradient technique has been used to optimise the fit. In the time domain the effusivity depth profile has been reconstructed [7, 8] and the neural network approach has been used to find the best fit [9].

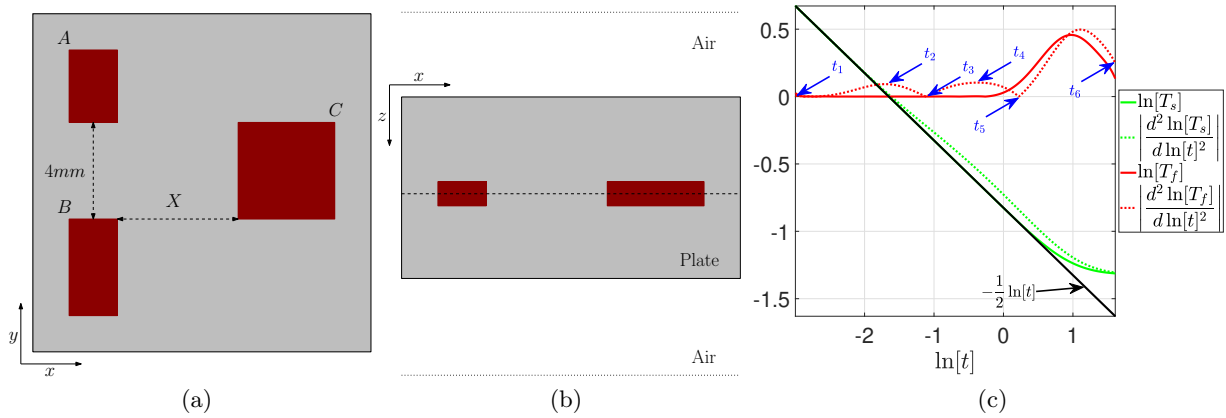


Figure 1: Sketch of the configuration in the xz -plane, (a) and in the xz -plane, (b). Thermograms in logarithmic scale for a sound area, T_s a flawed area, T_f and the absolute value of their second logarithmic derivatives.

In TNDT a successful characterisation of a subsurface defect consists of the knowledge of its location, its dimensions and its thermal properties. Our approach separates the characterisation of the defect in two stages: in the first stage, the localisation of possible defects and the reconstruction of their shapes in the xy -plane, see Fig. 1a, during the second stage, the estimation of their thickness and depth, see Fig. 1b, performed by using an iterative scheme.

2.1. Pre-processing

The temperature field inside anisotropic materials can be expressed mathematically by Eq. (1), where ρ, c represent the material density and heat capacity, respectively, κ_x, κ_y and κ_z represent the thermal conductivities in three principal directions. If the heating of the plate is instantaneous and on one side of the plate only, we can assume that the solution of temperature in flawless regions can be described by the one-dimensional heat equation $\frac{\partial T}{\partial t} = \alpha \frac{\partial^2 T}{\partial z^2}$, where $\alpha = \frac{\kappa}{\rho c}$ is the thermal diffusivity of the material. For an ideal pulse, heat flux uniformly applied to the surface of a semi-infinite solid, the temperature of the material at distance z from its surface is given by Eq. (2) where $\epsilon = \sqrt{\kappa \rho c}$ is the heat effusivity and Q is the energy supplied to the surface. The temperature at the surface of the sample is described by Eq. (3). From Eq. (3) is clear that the presence of any defect will be expressed as the deviation of the temperature decay curve from its expected values.

$$\rho c \frac{\partial T}{\partial t} = \kappa_x \frac{\partial^2 T}{\partial x^2} + \kappa_y \frac{\partial^2 T}{\partial y^2} + \kappa_z \frac{\partial^2 T}{\partial z^2} \quad (1)$$

$$T(z, t) = \frac{Q}{\epsilon \sqrt{\pi t}} e^{-\frac{z^2}{4\alpha t}} \quad (2)$$

$$T(t) = \frac{Q}{\epsilon \sqrt{\pi t}} \quad (3)$$

To get rid of experimental noise, pre-processing like thermographic signal reconstruction (TSR) leads to high spatial and temporal detection resolution [10]. The assumption of TSR is identical with the assumption of Eq. (3), which can be rewritten in the logarithmic scale as $\ln(T_{\text{surf}}(t)) = \ln\left(\frac{Q}{\epsilon}\right) - \frac{1}{2} \ln(\pi t)$ and expanded into a polynomial series:

$$\ln(T_{\text{surf}}(t)) = a_0 + a_1 \ln(t) + a_2 [\ln(t)]^2 + \dots + a_n [\ln(t)]^n. \quad (4)$$

where the logarithmic evolution of temperature at each pixel has been approximated by a n -degree polynomial function. This approximation compresses a thermographic sequence into $n + 1$ frames of polynomial coefficients, removes high-frequency temporal noise and enhances the defect visibility. Reconstruction of the signals in the logarithmic scale and the computation of second time derivative using the polynomial approximation derives time frames which are smoother and suitable for defect detection. Such detection can be carried out by different image processing algorithms, such as the Canny edge detection algorithm, to define the location, shape and size in the xy -plane of the defects. The application of these algorithms is out of the scope of the present communication and it will be addressed in a future work.

The choice of the polynomial degree is a trade off between accuracy of the approximation, noise management and computational time. Here the choice has been made by studying the behaviour of the second time derivative of the signals in the logarithmic space and re-sampling in time. Initially we choose the time instances where the absolute value of the second time derivative is zero and those where its value reaches local maxima between the zeros, see Fig. 1c. The first and the last time instances are also added. For t_N chosen time instances the polynomial degree will be set to be $n = t_N - 1$. In our case, as illustrated by Fig. 1c the absolute value of the second logarithmic derivative is zero at the beginning of time and in two more instances. By adding the instances where local maxima occur and the last time instance one has six time instances. Thus, the polynomial degree is set to be $n = 5$. For the configuration depicted in Fig. 1, and using noisy signals, $SNR = 20$, obtained in reflection we present the reconstructed images, Fig. 2, at the first four chosen time instances.

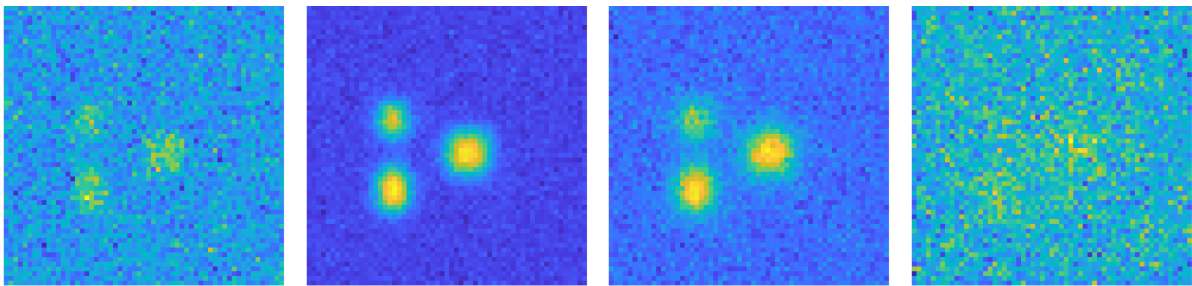


Figure 2: Reconstructed temperature field in the logarithmic scale for the first four chosen time instances, t_i , $i = 1, 2, 3, 4$.

2.2. Defect characterisation

In an inversion process, one usually minimizes a discrepancy between some experimental data, say u_d , and some model data, say u . The discrepancy function, also called cost or objective function, is often expressed as a norm of the difference between u_d and u . Most often, one uses the $L_2(\cdot)$ norm but since we are working with discrete data, the squared Euclidean norm is to

be used, $\mathcal{J} = f\left(\|u - u_d\|_2^2\right)$. The cost function is explicitly given in terms of u and minimized with respect to the parameters ψ , characterizing the flaws.

For the minimization problem the Levenberg–Marquardt method has been used [11]. This is an iterative method originally devised for solving non-linear least-square problems of parameter estimation but it has also been successfully applied to the solution of linear problems that are too ill-conditioned to permit the application of linear algorithms. The method decreases the ill-condition feature by using a “damping” parameter, $\ell \leq 0$, which may be adjusted at each iteration. Note that $\ell \rightarrow 0$ yields the Gauss-Newton algorithm while larger ℓ gives an approximation of the steepest descent gradient algorithm.

The forward model we use here models defects of delamination type as boundary conditions in a fictional interface inside the metallic plate. Thus, we are bounded to consider only flaws that are located at the same depth. The parameters to be estimated here are the depth at which the defects are located and their thickness. Thus, for the m detected flaws, the number of the unknown parameters will be $m + 1$, $\psi = (\psi_1, \psi_2, \dots, \psi_{m+1})^T$.

After applying TSR to the synthetic noisy data \mathbf{T}_{surf} , we end up with a three-dimensional matrix, denoted $\mathbf{T}_{p_x, p_y, n+1}$, containing $n + 1$ frames of $p_x \times p_y$ elements with the coefficients of the n -degree polynomials as expressed in Eq. (4). For each pixel we reconstruct the temperature signals in the logarithmic scale by evaluating the polynomials at the, previously chosen, time instances t_i , $i = 1, 2, \dots, n + 1$. The data to be fitted, denoted as u_d , is now the vectorised temperature in the logarithmic scale.

3. Experiment and result analysis

For the purpose of this research, the three-dimensional model [4] has been used to produce synthetic data, temperature signals, for the general configuration depicted in Fig. 1. A grade 4340 steel plate with thermal conductivity $k = 44.5$ W/mK, heat capacity $C_p = 475$ J/kgK, density $\rho = 7850$ kg/m³ and of thickness $d = 3$ mm is used. The steel plate has three well-defined air-filled defects, named A, B and C , to simulate delaminations of different thickness, $d_A = 3 \times 10^{-6}$ m, $d_B = 2 \times 10^{-6}$ m, $d_C = 1 \times 10^{-6}$ m and of different size $(2 \times 3$ mm), $(2 \times 4$ mm), $(4 \times 4$ mm), respectively. As an excitation term, a flash lamp depositing a heating power density of $Q = 10^4$ W/m² on the surface of the plate has been modelled as a Dirac’s delta function in time, whereas its spatial distribution is considered as uniform.

To test the robustness of the inversion scheme versus the noise, the configuration depicted in Fig. 1 has been tested for different noise levels using recorded signals in reflection, in transmission and in both situations. The thickness of the top and bottom layer, for this configuration, is $d_1 = 1.5$ mm and $d_2 = 1.5$ mm, respectively. The distance of the defects A and B from the defect C , which has been indicated as X in Fig. 1a, for this reference case $X = 5$ mm. The parameters to be estimated are the thickness of the defects and the depth in which they are located, d_A, d_B, d_C and Z respectively.

The relative error of the estimation of the parameters is shown in Fig. 3 for each parameter as a function of SNR. As one can see, the estimation is highly depending on SNR but also on the used signals. That is, using the signals obtained in transmission, a better estimation can be achieved than using the signals in reflection. Yet the usage of both signals does not ensure a better estimation as one can see in Fig. 3a and in Fig. 3b where for SNR equal to 40 or 30 the estimation is not given with a smaller relative error as in the case of using only the signals recorded in transmission.

From Fig. 3 one can understand the nature of the estimated parameters and how their estimation can be affected by the signals used. From these graphs it is clear that the best estimation of the defects depth can be achieved by using both recorded signals, *i.e.* in reflection and transmission, and the worst one by using only the signals in transmission, see Fig. 3d. The

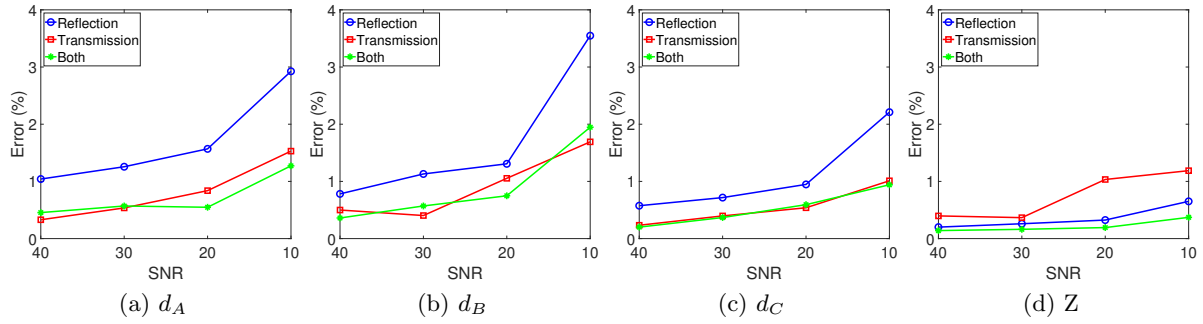


Figure 3: Relative error for the estimation of four parameters as a function of SNR.

latter is not true for the estimation of the defects' thickness as it is clear from Fig. 3(a),(b),(c) where the estimation is better using the signals in transmission than in reflection.

By using the configuration depicted in Fig. 1a as a reference, we want to test the performance of the inversion scheme in difficult situations. Such a situation can be when the defects are located close to the top or bottom surface of the plate. The depth of the defect, *i.e.* the distance of the defects from the upper surface of the plate, has been changed to 0.75 mm and 2.25 mm while the noise level has been kept constant, $SNR = 20$.

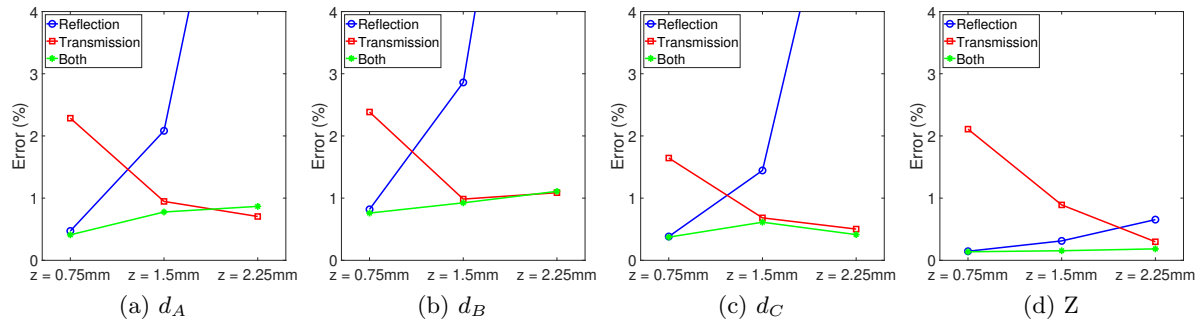


Figure 4: Relative error for the estimation of four parameters as a function of defects' depth.

The estimation of the parameters d_A , d_B and d_C is strongly affected by the depth of the defects as one can see in Fig. 4. For the configuration where the defect is deeply buried in the plate, $z = 2.25$ mm, the estimation of the thickness is very poor using the signals in reflection, relative error higher than 10%, but very accurate when using the signals in transmission. On the other hand, when the defects are close to the upper surface, the estimation accuracy is not significantly affected. As for the estimation of the defects' depth, for the buried defects the estimation accuracy is better using signals in transmission whereas in the case of the defects being close to the upper surface of the plate the estimation is better using signals in reflection. These results agree with the physics of the problem.

An interesting configuration where the advantages of using a three-dimensional forward model can be fully exploited is that of defects located close to each other. Keeping as reference the configuration depicted in Fig. 1a, we set up two new configurations by setting the distance of the defect named C from the other two to 2 mm and 0 mm respectively. The noise level has been kept constant, $SNR = 20$. In this kind of configurations, where the interaction between the defects is strong, the one-dimensional approaches fail to characterize accurately the defects. The advantage of using a three-dimensional model can be exemplified by Fig. 5 where one cannot find a strong link of the estimation accuracy and the defects' relative location in the xy -plane.

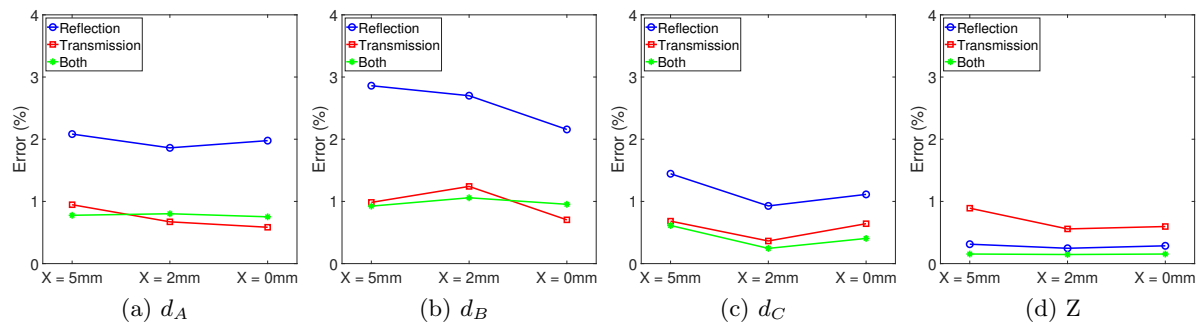


Figure 5: Relative error for the estimation of four parameters as a function of the relative distance X between to defects A, B and C .

4. Conclusions and perspectives

This contribution presented a model-based inversion strategy for thermographic characterisation of delamination in planar pieces. We choose to use here the Levenberg–Marquardt method where, as an iterative method, its performance is strongly linked to the forward model. In this work we use a three-dimensional semi-analytical model based in the TREE approach which is fast and accurate. Results of the inversion scheme, using synthetic noisy data, have been presented in the work for several cases.

In the future we intend to extend this work by considering more complex cases. Thus, the used forward model has to be enhanced. Flaws with more complex shapes in the transverse plane have to be introduced in stratified planar geometries for modelling delamination in composites. Surface defects, crack-type, will be introduced to the model using the Green function. Moreover, the application of signal processing tools as the Canny algorithm will be addressed in order to compute the transverse location and the shape of the flaws.

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