Optimized robotic setup for automated active thermography using advanced path planning and visibility study

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Received 20 December 2017; revised 14 March 2018; accepted 14 March 2018; posted 15 March 2018 (Doc. ID 318171); published 20 April 2018

In-line inspection of advanced components remains a challenging task in industry. The authors will describe an automated methodology that uses numerical simulations to automatically determine the best set of experimental parameters to inspect the structure on defects using active thermography. The inspection is performed using a robotic arm and advanced path-planning tools to determine the optimal positions of the measurement points and excitation points. During the path planning, the directional emissivity is considered for the complex surface, and a minimization of the amount of measurement points is performed. The numerical simulation optimization used a genetic algorithm and spline regression model to optimize the heat power, robot speed, camera frame rate, and excitation timing to fulfill the automatic inspection. © 2018 Optical Society of America

OCIS codes: (160.2220) Defect-center materials; (120.4290) Nondestructive testing; (120.6810) Thermal effects; (000.4430) Numerical approximation and analysis; (000.6850) Thermodynamics.

<https://doi.org/10.1364/AO.57.00D123>

1. INTRODUCTION

Active thermography is a broadly used technology to inspect large, carbon-fiber-reinforced plastic (CFRP) components for flaws in a fast way [1,2]. To receive accurate results on large samples, the thermal camera has to be repositioned over the structure in a way that each surface is inspected with sufficient accuracy with an equal heat excitation and time resolution considering directional emissivity, discrete measurement positions, and historical heating patterns [3,4]. To perform these sequential experiments in a robust, repetitive way, multiple techniques are developed that mount a thermal camera and/or excitation source to a robotic arm to control the relative position and speed of the inspection unit versus the inspected structure [5–7].

Automatic scanning using a robotic arm is seen as an interesting way for non-destructive testing (NDT) of large and complex-shaped components [4]. However, the programming of the inspection path, speed, excitation power and duration, and excitation orientation and acquisition rate is a difficult task that is highly dependent on the inspected sample geometry, material properties, and interested depth resolution [4,8,9]. This parameter optimization is mostly done manually by a highly qualified inspector using experience and trial and error,

which is a time-consuming task for complex structures, as the heat deposition and scanning speed should match the heat diffusion in the material [8].

Within this paper, the authors will use recent advances in thermal model updating techniques [3] in combination with a numerical directional emissivity estimation [10] integrated in a novel approach for robotic path planning, which is based on model-based view-planning algorithms [11]. The potential of the combination of those techniques will be shown on a technically challenging structure to inspect using active thermography: a CFRP bicycle frame. Active thermography inspection is seen as a promising technique for CFRP bicycle frame inspection [12]. Especially due to the anisotropic material properties and large surface containing small tubular shapes, those inspections are challenging to optimally automate.

2. EXPERIMENTAL MEASUREMENTS

The goal of this paper is to inspect a CFRP bicycle frame in order to estimate the tube thickness and inspect for defects such as cracks and delaminations using a 6 deg of freedom (dofs) industrial robotic arm (Kuka Kr16), controlled using a robotic operating system (ROS) with MATLAB, a micro-bolometric thermal camera (7–14 μm , 640 $\times$ 512 pixels, 12 mm lens),

Fig. 1. Robotic thermal inspection.

and an optical excitation source of 500 W for pulsed thermography. A time-of-flight and visual camera are used for the precise position correlation and hand-eye calibration among the experimental measurements, robot, and the computer-aided-design (CAD) geometry. The bicycle frame is painted in the team colors and the tubular shapes and metallic inserts result in a challenging structure to evaluate. It is the aim to illuminate the structure as homogeneously as possible using advanced path-planning techniques and to simplify the numerical model. The setup is shown in Fig. 1.

3. METHODOLOGY

Within this section, the methodology is described in order to find the optimal set of measurement parameters, found in Table 1. The retrieved results are discussed in Section 4. Finite element (FE) model updating is used to optimize the complex parameter set of the robotic thermography setup by correlating the numerical results with NDT data. Similar methods are widely used in modal vibration inspection [13,14], but their usage is limited in thermal optimization problems [15] due to the difficulties in, e.g., estimating the diffusivity [10]. The first step, the development of the numerical model, is done in Comsol Multiphysics 5.0 combining transient heat transfer with multibody dynamics and in combination with Siemens Simcenter 3D for the meshing of the composite laminates structure. The anisotropic thermal conductivity through the CFRP layers and influence on the global thermal diffusivity are considered. The used numerical model is further described in Subsection A. For the optimization of the experimental parameters, there is made use of a finite element model updating (FEMU) technique, based on spline-based regression to decrease the computational needs of the numerical simulations in combination with a genetic algorithm optimization routine. The principle can be found in [3], and more details are given in Subsection B. The optimal set of measurement parameters is used to locate the measurement inspection positions. The path through these points is optimized using the path-planning and visibility study, further described in Subsection C. The last step contains the data capture and post-processing to translate appearing temperature to laminate thickness, which is defined in Subsection D.

A. Numerical Simulation

The numerical model of the bicycle frame is built from a 3D scan. The 3D scan is measured by a Creaform 3D scanner. The resulting stereolithography (.stl) file is cleaned and used to build a 2D structured mesh of CQUAD elements using the Siemens

Table 1. Optimization Parameter Limits

	Lower Limit	Upper Limit
Excitation power [W]	100	500
Excitation duration [s]	2.0	20
Frame rate [Hz]	5.0	50

Fig. 2. Overview of the 2D CQUAD mesh on the bicycle frame.

Simcenter 11 software using a global element size of 5 mm. The 2D mesh forms the basis of the laminate mesh, which is extruded to a 3D mesh of the tubes. A representation of the 2D mesh is shown in Fig. 2. The laminated properties of the bicycle frame are approximated using a five-layered laminate consisting of:

- 1 thin uniform layer for the paint cover of 0.11 mm thick,
- 1 CFRP layer of 25% of the thickness with a global fiber orientation of 0°,
- 1 CFRP layer of 25% of the thickness with a global fiber orientation of 90°,
- 1 CFRP layer of 25% of the thickness with a global fiber orientation of 90°,
- 1 CFRP layer of 25% of the thickness with a global fiber orientation of 0°.

With this stacking order, a symmetric quasi-isotropic laminate is represented. As the precise stacking and layer properties are unknown, it is assumed that the represented stacking can be considered sufficiently accurate as input for the material parameter optimization process where the global thermal diffusivity properties are updated with respect to adequate measurements. A detailed picture of the 3D mesh with the different layers is shown in Fig. 3. The mesh consists of 28,623 elements with structured material orientation according to the laminate properties. The metal inserts are neglected, as they are positioned far away from the evaluated measurement areas. In contrast to the mesh generation, the numerical analysis is performed using Comsol Multiphysics 5.0 to facilitate the interaction with the optimization routine using MATLAB.

A tubular halogen excitation source is used. This excitation source results in a non-homogeneous spatially distributed heat excitation, which is shown in Fig. 4. This spatial distribution should be implemented in the excitation source modeling to correlate the heat distribution on the inspected test sample

Fig. 3. Overview of the 3D mesh with the different plies schematically represented by different colors.

Fig. 4. Spatial temperature distribution of the heat source.

accordingly. Besides a spatial non-homogeneity, the thermal time constant results in a different distribution related to the type and history of the heat source, which should be considered in the numerical model. For the used halogen excitation units, this is shown in Fig. 5. It is clearly seen that the excited radiation is delayed from the initiated trigger signal due to the thermal inertia. To accurately correlate the numerical model with the experimental data, this thermal inertia can be considered by correcting the input signal with the thermal response.

1. Physical Boundary Conditions

The governing differential equation is a combined heat transfer equation with conduction, convective cooling, and radiation of

Fig. 5. Excitation output Halogen source.

an external heat source, formulated in Eqs. (1)–(3) where ρ is the density, C_p is the heat capacity at constant pressure, T is the absolute surface temperature, κ is the thermal conductivity, t is the time, $Q(t)$ is the time dependent heat source, h is the coefficient of convection, ε is the emissivity, and σ is the constant of Stefan–Boltzmann [16,17]:

$$\rho C_p \frac{\partial T}{\partial t} + \nabla \cdot (-\kappa \nabla T) = Q \quad (1)$$

with $T(x, y, z, 0) = T_\infty = 292.88 \text{ [K]},$

$$\kappa \nabla^2 T = h(T_\infty - T), \quad (2)$$

$$\kappa \nabla^2 T = \varepsilon \cdot \sigma \cdot (T_\infty^4 - T^4). \quad (3)$$

The external heat source is simplified as a boundary heat source with properties as described above. The non-linear characteristics are shown in Figs. 4 and 5.

A few assumptions are made:

- The air velocity is assumed to be zero allowed by the laboratory conditions.
- The lay-up of the CFRP laminate is considered quasi-isotropic with random fiber angles in a woven pattern.
- The test sample is opaque and behaves like an ideal gray body as a result of the black paint coating. The yellow paint covers are neglected within this simplified model.

2. Solver Parameters

A constant Newtonian non-linear method is used with a modernized implementation of the differential algebraic equation (DAE) solver, which uses the backwards differential formula (BDF) [18]. Also, linear Lagrange elements are used to simulate the transient time-dependent heat radiation from an external source to the inspected surface and the emitted response of the surface [19]. The initial step size is taken at least 10 times smaller than the experimental frame rate, and the maximum step size is equal to the used frame rate. The variable values within the computed matrices are scaled iteratively within the solution to compute the non-linear effects more precisely.

B. Optimization Routine

The thermal excitation power, excitation duration, and thermal camera frame rate are selected as optimization parameters. The laminate thickness z is evaluated in the objective function [Eq. (4)] and has physical boundary conditions. The laminate thickness z can be computed from the thermal response according to [Eq. (5)], with α the global thermal diffusivity as a combination over the different layers; f_b is the blind frequency, and C_1 is the correlation constant, which is typically equal to 1.82 as presented by [20]. This is further described in [9]. The parameter limits, used within the optimization, are shown in Table 1. For each measurement point, there are used three initial values for each optimization parameter, based on the central composite design: lower boundary, upper boundary, and center value:

$$\ell(\vartheta) = z_{\text{model}}(\vartheta) - z_{Ex}, \quad (4)$$

$$z = C_1 \sqrt{\frac{\alpha}{\pi \cdot f_b}} = C_1 \cdot \mu. \quad (5)$$

The optimization routine makes use of an adaptive response surface (ARS) optimization to optimize numerical models with a large number of data points. The regression model is built from a multidimensional linear interpolation of scattered data using the previously performed FE simulations within the design space [21]. The routine is designed to handle multiple-output time series data [3]. The optimization procedure can be divided into the following steps:

1. Starting reference simulation points are performed, and a correct object function is built of the difference between the FE model and the optimal target values defined in the objective function.
2. The FE model is replaced by an interpolation-based meta-model of response surfaces to decrease the optimization time but remains an accurate approximation.
3. The optimization routine is run on the specific object function to find the minimum for the meta-model. There is made use of an optimization routine based on a genetic algorithm computation to find the optimum fast for the complex numerical model. The genetic algorithm optimization routine is inspired by the natural evolution theory of Darwin applied to populations to optimize a function [22]. It is chosen to perform gray encoding to avoid fictive boundaries between consecutive values [23]. The speed of convergence is the main drawback of the method, although, in perspective with the time consuming FE model, the optimization remains neglectable due to the complexity of the FE model. The significant advantages of using a genetic algorithm are the high probability of global minimum detection and the ability to fit non-smooth objective functions. As the thermal pulse is discrete, the temperature distribution over time has a non-smooth time step where the heat source is switched off [24].
4. The estimated parameter values are used as input parameters for an improved FE model that corrects the meta-model.
5. Only the points closer to the minimum are used to form the response surface (pan and zoom function).

The response model that is optimized is not built from a pre-defined number of design experiments, but is adapted and refined during the optimization routine by a pan and zoom command [3]. The method automatically calculates the parameter influence sensitivity and sequentially resolves multiple sets with first the major influencing parameters with fixed parameter values for the minor influencing parameters. Succeeding, the second parameter set is optimized, and finally an influence check is performed for all parameter sets until the results converge. The uniqueness of the optimization routine is verified by performing an ill-posedness analysis. A global minimum of the objective function can be found and results in a unique solution in the region specified by the parameter limits. The stability of the convergence of the optimization solutions is difficult to prove. Using the ARS method, a global solution of the results is achieved by starting from the different corner values in the parameter design space of the initial central composite design together with the central coordinate of the parameter set, built from the parameter boundary values, as shown in Table 1. If a

majority of the initial starting points deliver the same result, it is used further in the optimization routine [3]. This strategy is verified on numerically simulated data and standard flat bottom hole test samples with homogeneous material properties in [3]. A comparison of the implementation of different optimization routines is shown in [25].

C. Path-Planning and Visibility Study

The path planning is dependent on the directional emissivity of the CFRP bicycle material. The directional emissivity, dependent on angle θ , is found according to [10] following formula Eq. (6).

The directional emissivity will be approximated with

$$\varepsilon(\theta) = \max(\cos(p_1\theta + p_2 * \pi), 0), \quad (6)$$

where p_1 and p_2 are fitting parameters, found using a numerical model updating according to [10] as, respectively, $\sqrt{1.6}$ and 1.115π . The normal maximum emissivity is $\varepsilon = 0.85$ due to the paint cover.

The authors obtain an efficient scanning trajectory by performing a two-stage process. First, the authors obtain an initial path guaranteeing coverage and measurement constraints. And second, the authors optimize this path by a gradient-based inspection path optimization strategy to reduce the path complexity detailed in [26].

To automatically determine an initial scanning trajectory the authors use a greedy *generate and test procedure* similar to [11]. The authors first compute a set of candidate viewpoints by dilating uniformly sampled surface points from the object by an ideal scanning distance. These viewpoints are checked on reachability by the used robot, and unreachable viewpoints are removed. For every candidate viewpoint, the directional emissivity is calculated for visible surface points, which are dependent on the scanning angle. The viewpoint with the best average directional emissivity is selected over the model points that are used in the thermal simulation. This optimal value is stored as the current measurement state for each surface point. This step is then repeated until the stopping criteria are met. These stopping criteria can be “maximum coverage reached,” “optimal emission map found,” or “maximum number of viewpoints reached.” The solution of this set-covering problem contains the set of viewpoints that should be reached during the measurement. In a final step, the traveling salesman problem is solved among all candidate viewpoints.

Because of the greedy nature of the scanning trajectory initialization, we end up with a sub-optimal path. The authors improve this initial path by performing a local inspection path optimization to improve the quality of the final path [26].

The quality of the final path is highly dependent on the positioning of the bicycle frame due to collision risk. Therefore, the authors efficiently sample the configuration space of the bicycle frame and compute a trajectory for each position. The position that delivers the best scanning trajectory is automatically selected. At each measurement pose, multiple images are captured defining one data cloud. The experimental setup is developed according to Fig. 1 where the experimental parameters defined in Table 1 were used as input parameters of the optimization routine.

Fig. 6. Qualitative result of active thermography measurement after post-processing.

D. Data Processing

The time-of-flight and color image are used for geometric localization and calibration purposes. There is made use of long pulsed thermography with 40 prior cold frames captured to eliminate reflections and local emissivity. The measurement sequence contains 5 s of excitation followed by 20 s of cooling down, measured at 40 Hz. The power of the excitation source is set on the maximal power of 500 W. The data is post-processed using pulsed-phase thermography (PPT) to estimate the thickness using Eq. (5) and the methodology described in [9]. A post-processing result of a performed full-field measurement on the bicycle frame is shown in Fig. 6, in which different interesting areas are shown, which indicates a non-homogeneous tubular thickness.

4. RESULTS AND DISCUSSION

Due to the path-planning and visibility study, the authors achieved to perform sequential measurements in order to perform uniform automated pulsed-thermography inspection. The inspection path defined is shown in Fig. 7. Thereby,

Fig. 7. Final path covering 85% of the surface of the bicycle frame. The colorbar is the expected emissivity.

Fig. 8. Visualization of the measurement setup with one example measurement pose and the therefore expected relative radiosity seen by the camera.

85% of the full frame surface is seen in at least one position. The maximal directional emissivity is shown in the color scale. An overall emissivity of 0.82 is expected. It is considered that support of the frame is needed, and the best position therefore is seen as the bottom of the frame. The emissivity on the best position is plotted in color on the frame. Thereby, the numerical model can be simplified to a uniformly distributed boundary heat source on the surface of the bicycle frame considering the emissivity map in Fig. 7. The simulated measurement setup with the field of view and expected radiosity is seen in Fig. 8 for one of the measurement positions. By comparing the results of certain regions with the global coverages in Fig. 7, a weighting of the local results of the temperature readings can be made with respect to the emissivity. For all data points, the measurement position with the maximal emissivity value is selected to perform the depth estimation. Overlapping data points are used only for verification. The resulting path is optimized iteratively to a minimized path length and to minimize the amount of measurement positions. The numerical simulation model is further used to estimate the necessary excitation power and excitation pulse time needed to optimally measure the local tube thickness of the frame, considering an anisotropic fiber distribution through the laminated plies. The numerical model that is used within the optimization routine is shown in Fig. 9. The model consists of three different material mesh collectors: one for the covering paint with a thickness of 0.11 mm and two for the CFRP plies with a consecutive 90 deg angle between each ply and with the respective global orthotropic ply material properties. Within the initial assumption, the full bicycle frame has a continuous thickness of four CFRP plies in a regular stacking: [0,90]_s. The material properties and heat exchange properties are defined using the numerical updating progress, as described above in comparison with a preliminary static measurement. A representing result on one measurement position using the robotic inspection is shown in Fig. 10, where a crack

Fig. 9. Numerical finite element model result after 1 s, temperatures in °C.

Fig. 10. Measured crack.

including surrounding delaminations is shown. The thickness of this area is difficult to compute due to the crack and delaminations. The crack will show a thickness of 0 mm, which is below the lower limit. Also, the delaminations have a thickness close to the minimal thickness. In reality this can represent the local useful thickness of the tube. The local thickness of different points is examined in comparison to some benchmark points that are possible to physically measure. The measurements are performed with an accuracy of 20 μm and shown in Table 2. It can be seen that the accuracy of the estimated thickness is accurate for the three inspected points that can be validated with physical measurements. This gives confidence to the two values that cannot be verified without destroying the

bicycle frame and proves the assumption that it is possible to define a measurement inspection routine by using advanced path planning in combination with thermal FEMU routines for complex-shaped composite materials.

5. CONCLUSIONS

Within this paper, it is shown that the implementation of a thermal numerical model updating routine with advanced visibility analysis and robotic path planning can provide accurate, automatic active thermography inspection without the need of an iteratively trial-and-error setup. It is shown that thickness evaluation of complex-shaped structures is feasible. A well-defined hand-eye calibration between the cameras is needed to accurately map the thermal information on the CAD geometry. Also, the inspected structures should be known to determine quantitative results. Opportunities arise for industrial implementation in serial production of complex-shaped structures for zero-failure quality prediction.

Funding. Universiteit Antwerpen (UAntwerp); Agentschap voor Innovatie door Wetenschap en Technologie (IWT) (HBC.2017.0032); Fonds Wetenschappelijk Onderzoek (FWO) (V4.010.16N, 1S.262.16N); University of Antwerp Industrial Research Funds (UAntwerp IOF) (34924).

Acknowledgment. The fundamentals of this work were presented at the AITA conference, Quebec-city in 2017, paper: Optimized setup modification for automated active thermography. The authors would like to thank the organizing committee for selecting the work for its Under 35 Paper Award «Ermanno Grinzato» 2017. This research has been funded by the University of Antwerp and the IWT-VLAIO by the support to the TETRA project “Smart Integration of Numerical modeling and Thermal inspection (SINT).” The authors would like to end with a special thanks to the MiViM research Chair of Prof. Xavier Maldague and the support of the full team in supporting the preliminary measurements of this research.

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Table 2. Optimization Results

	Real Value	Computed Value
Saddle tube (top) [mm]	2.64	2.32
Head tube (top) [mm]	4.05	4.05
Lower tube (middle) [mm]	2.05	1.95
Top tube (middle) [mm]	?	2.21
Rear tube (middle) [mm]	?	3.61

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