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ADAPTIVE TFM IMAGING IN ANISOTROPIC STEELS USING OPTIMIZATION ALGORITHMS COUPLED TO A SURROGATE MODEL

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ABSTRACT

An optimization method is studied to enhance the reliability of TFM (Total Focusing Method) images in anisotropic nuclear materials. The method is able to adapt to a given anisotropic structure (weld, cladded steel) when the parameters governing the wave propagation are uncertain. The optimization scheme combines a surrogate model to bypass the extensive computation times of the propagation forward model, and a gradient descent algorithm to minimize a multivariate cost function. The gradient-based optimization is compared with a global optimization tool, the Particle Swarm algorithm. Finally, the parameters (stiffness constant, grain orientation, cladding thickness…) corresponding to the optimal TFM image are compared with those measured by other characterization techniques.

Keywords: Ultrasonic imaging, Total Focusing Method, Anisotropic materials, Uncertainties, Surrogate-model, Optimization algorithm.

1. INTRODUCTION

Ultrasonic inspection of coarse-grained materials, castings and austenitic welds commonly found in nuclear installations is one challenging problem in NDT, in particular due to the a priori uncertainties on the microstructural characteristics. Several approaches have been proposed in the literature, to deal with these uncertainties especially in the case of austenitic welds. One common approach to deal with these uncertainties consists in the adjustment of the parameters of a welding description model with iterative optimization procedures based on simulated signals or fast ray-tracing algorithms. Generally, the weld map is obtained with a pre-characterization step before imaging and involves a specific experimental setup [1]. Another approach relies on the prior knowledge of a reflector inside the medium, which serves as standard to an optimization scheme that improves the reliability of images based on some well-chosen quality estimators [2]. Thus, imaging and characterization of welds are two simultaneous processes requiring only one experimental setup. The method presented hereafter relies on this latter strategy, except that the reflector properties are not assumed to be known at the time of inspection.

The work presented in this communication is achieved in the framework of the European project ADVISE. It aims to develop optimization algorithms for TFM (Total Focusing Method) imaging of anisotropic materials without prior information on their properties. The optimization procedure is based on an iterative local (Gradient Ascent) or global (Particle Swarm) algorithm which maximizes a multivariate cost function defined from image-quality estimators. Each iteration step updates the material properties to provide new images until convergence criteria are satisfied. The optimization method requires a single set of experimental data to form a large number of TFM images. The times of flight needed for TFM imaging are computed from the ray-tracing algorithm of the CIVA software. In order to reduce the computation times, a surrogate model is used to bypass the imaging algorithm.

In this communication, we illustrate this method on experimental data acquired on various mock-ups: cladded components and anisotropic welds of varying degrees of complexity. Extracted properties from the optimization method are compared with those measured by other characterization technics (ultrasound, X rays, EBSD…).

2. PRINCIPLE OF THE ADAPTIVE IMAGING

Let us consider a specimen where the wave propagation is strongly influenced by its anisotropic properties. One can define a number Q of critical parameters to which the TFM images are sensitive. For instance, in an austenitic weld described by the Ogilvy parametric model, the grain orientation gradient and the elastic tensor may be critical parameters. In the case of a stainless steel cladding, assumed to be anisotropic and homogeneous, images are sensitive to the cladding elastic properties and thickness. When the values of those parameters are uncertain, the TFM images can be significantly degraded (low signal-to-noise ratio, positioning errors, false calls…). In those cases, the implementation of an optimization algorithm can be helpful.

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A criterion is needed to define the accuracy of the computed image when imaging a potential defect. The descriptor considered in this study is the maximum amplitude of the TFM image, noted Amax. Indeed if the material parameters are misestimated, the recorded signals do not focus to well-form the defect echo, decreasing the Amax value.

The proposed optimization scheme is an iterative process whose initial step assumes an isotropic medium. A surrogate model is implemented to interpolate a *Q*-dimension database of experimental images, saving costly forward computations of images at each optimization step. The Kernelized Ridge Regression (KRR) combines the advantages of the Kernel Trick with a Ridge Regression [3], overcoming the curse of dimensionality encountered in the studied cases. The KRR consists in the minimization:

$$\min_{\boldsymbol{w}} \left(\|\boldsymbol{Xw} - \boldsymbol{Y}\|^2 + \lambda\|\boldsymbol{w}\|^2\right). \quad (1)$$

$\boldsymbol{w}$ are the model weighting coefficients, designed by a chosen kernel, $\boldsymbol{X}$ and $\boldsymbol{Y}$ are the input and output parameters of the model, respectively. The regularizing term λ penalizes the variance of $\boldsymbol{w}$. In the present case, the KRR model well predicts the Amax-estimator for a selected database within specified dataset limits.

After interpolating the database, this study investigates the ability of two different algorithms to produce optimized images. The first algorithm is a modified Gradient Ascent Optimization (GAO):

$$\boldsymbol{X}_{j+1} = \boldsymbol{X}_j + \eta_j \boldsymbol{\nabla}\mathrm{f}(\mathbf{X}_j), \quad (2)$$

with η_j the learning rate at step j of the gradient ascent, which follows a decaying law as j increases. To ensure a reliable convergence, the decaying learning rate is associated with a periodic warm restart similar to what is presented in [4]. The gradient is locally computed using centered finite differences. The second algorithm is a classical Particle Swarm Optimization (PSO) [5], where each randomly initialized particle of the swarm obeys:

$$\boldsymbol{X}_{j+1} = \boldsymbol{X}_j + \boldsymbol{V}_{j+1}\,, \quad (3)$$

where $\boldsymbol{V}_{j+1}$ is the inertia of the particle at step $j+1$:

$$\boldsymbol{V}_{j+1} = \alpha\boldsymbol{V}_j + \beta(\boldsymbol{P}_i - \boldsymbol{X}_j) + \gamma(\boldsymbol{P}_g - \boldsymbol{X}_j)\,. \quad (4)$$

The $\boldsymbol{P}_i$ and $\boldsymbol{P}_g$ points respectively correspond to the best particle and to the best swarm positions. The α, β and γ coefficients are chosen in order to penalize or not the displacement of a particle with respect to $\boldsymbol{P}_i$ and $\boldsymbol{P}_g$. The convergence is assumed when particles communicate with each other while traveling across the quasi-concave *Q*-dimension space. The PSO algorithm was also implemented to assess that GAO algorithm correctly converges.

3. RESULTS AND DISCUSSION

The optimization algorithms were evaluated on two mock-ups. The first mock-up is a ferritic steel bloc with an austenitic cladding, and the second one is a large weld mold (provided by Electricité de France, EDF), whose dimensions exceed the array aperture. Both experimental setups are schematized in Fig. 1. In the two cases, the optimization problem is simplified as the materials are considered orthotropic and homogenous and the surface geometries are planar. The FMC data were recorded with a linear transducer array, assuming a 2D wave propagation problem, thus reducing to only 4 elastic components to account for anisotropy.

In addition to the elastic parameters, the thickness h of the austenitic cladding and the grain orientation θ in the weld mold must also be optimized, as it remains uncertainties about their true values.

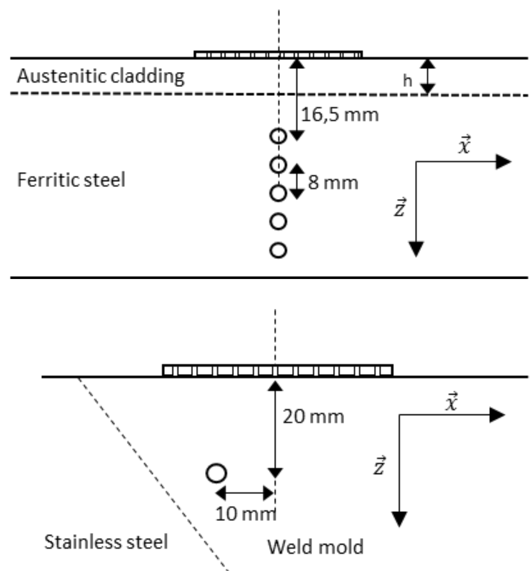

FIGURE 1: INSPECTION OF A CLADDED COMPONENT (TOP) AND AN AUSTENITIC WELD (BOTTOM) WITH A CONTACT LINEAR ARRAY

The TFM images computed before (isotropic assumption) and after the optimization procedure are given in Fig. 2 for the cladded component and in Fig. 3 for the weld mold. For both materials, the images are issued from the GAO (the images obtained from the PSO algorithm being identical). A comparison between the values of the 5 optimized parameters and their reference values obtained with other measurement techniques is given in Fig. 4.

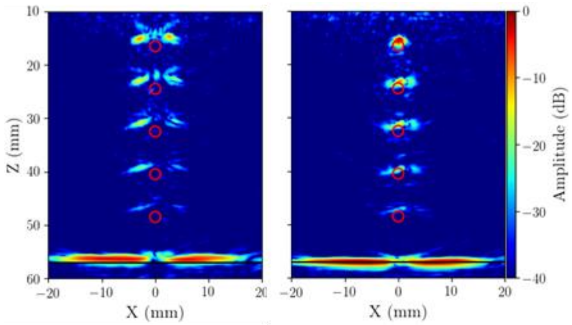

FIGURE 2: TFM IMAGES IN THE CLADDED COMPONENT WITH AN ISOTROPIC RECONSTRUCTION MODEL (LEFT) AND WITH THE GRADIENT-BASED OPTIMIZATION METHOD (RIGHT)

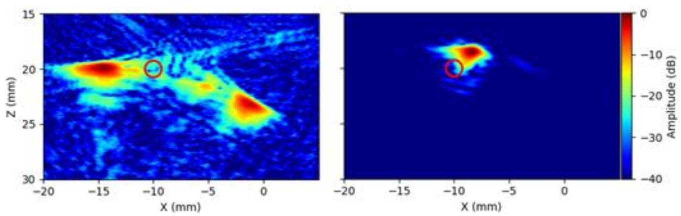

FIGURE 3: TFM IMAGES IN THE WELD MOLD WITH AN ISOTROPIC RECONSTRUCTION MODEL (LEFT) AND WITH THE GRADIENT-BASED OPTIMIZATION METHOD (RIGHT)

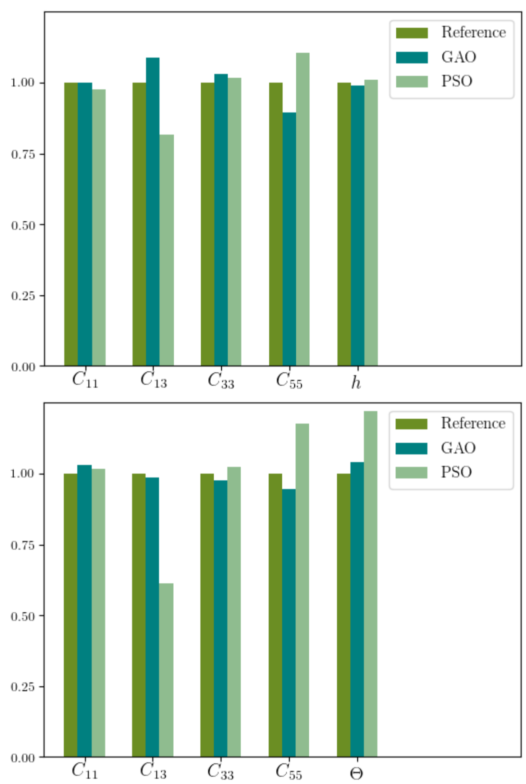

FIGURE 4: COMPARISON BETWEEN THE REFERENCE AND OPTIMIZED NORMALIZED VALUES OF THE PARAMETERS DESCRIBING THE CLADDING LAYER (TOP) AND THE WELD MOLD (BOTTOM)

The results in Figs. 2 and 3 show a tremendous improvement of the TFM images after optimization with the GAO algorithm. The phenomenon of splitting echoes is corrected and the position of each echo is very close to the position of the corresponding defect, making this tool appropriate for adaptive imaging.

The elastic parameters issued from the GAO and PSO results are compared in Fig. 4 to the values given by independent characterization methods and considered as reference values (the optimized values are normalized by the reference ones). It appears that the parameters issued from GAO and PSO are mostly close to the reference ones. For example, as regards the weld properties, the estimation of C_{33} gives 205 and 215 GPa with GAO and PSO, respectively, while the reference value is 210 GPa.

Despite differences in the estimation of parameters C_{13}, C_{55} and θ, it has been observed that both algorithms produce almost identical images. The differences between these values are due to the non-uniqueness of the solution as the problem is ill-conditioned

4. CONCLUSION

This study demonstrates the feasibility of an adaptive procedure for TFM imaging in the case of uncertainties on the elastic properties of an anisotropic material. The results obtained here on homogeneous anisotropic materials are quite encouraging and the next step will be to test the method on more complex materials exhibiting inhomogeneous anisotropic properties.

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