An Efficient Numerical Scheme for Sizing of Cavity Defect in Metallic Foam from Signals of DC Potential Drop Method

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***Abstract*—Quantitative Nondestructive Testing is important to guarantee the integrity of Metallic Foam (MF) structure. To predict the profiles of a cavity defect in MF material, a database type fast forward scheme is upgraded at first by introducing a multi-medium finite element for the efficient simulation of DC potential drop (DCPD) signals of MF with defect of complicated shape. Second, a hybrid strategy of neural network (NN) and the conjugate gradient optimization method is developed to obtain the size and position parameters of the defect. Both simulated and measured DCPD signals are adopted to reconstruct the bubble defect in aluminum MF. The good agreement of the true and the reconstructed values demonstrated the validity of the new scheme.**

***Index Terms* — Nondestructive testing, inverse problem, finite element methods, artificial neural networks, numerical analysis.**

I. Introduction

Metallic foam (MF) of high porosity has potential applications in many key engineering fields due to its features such as super-light, high specific strength etc. However, cavity defect of large size may occur in MF during its fabrication. To guarantee the material quality, a non-destructive test (NDT) tool is necessary to detect and evaluate cavity defect of size exceeding permission [1]. DC potential drop (DCPD) method, of which the feasibility has been demonstrated via both numerical analysis and experiments [1]-[2], is considered as an important NDT technique for the real-time quality assessment of MF. For inverse analysis, an efficient numerical simulator of high precision is indispensable. The conventional methods, however, are not suitable for complex-shaped defect as it is difficult to be modeled with a normal finite element.

In this work, a multi-medium element (MME) is introduced for the simulation of DCPD signals due to a volumetric defect of complicated shape. In addition, the database type fast simulation code developed by authors is upgraded to treat volumetric cavity defect based on the MME for the time-saving of forward analysis. Inversion problem of flaw characterization has been studied by authors in [1] with DCPD signals for MF, and authors in [3-4] with eddy current (EC) signals for metallic plates. Besides, hybrid inverse scheme, inversion scheme consist of two or more methods, like the combination of artificial NNs (ANNs) and the fuzzy logic (FL) developed in [5], the least square (LS) algorithm combined with the radial basis function NN (RBFNN) method in [6], are used for better flaw characterization. In order to avoid being trapped in a local minimum of the error function, good initial flaw estimates are generated by a NN signal-processing system by authors in [7]. Inspired by authors in [5-7], a hybrid inverse scheme combining the conjugate gradient (CG) method and NN method is introduced for the defect sizing from DCPD signals within this work. Both the upgraded fast solver and the hybrid inverse analysis scheme are validated by reconstructing defect profiles from simulated and measured DCPD signals.

II. Hybrid Inversion Method

The hybrid inversion scheme combines the CG method and the NN method. As large number of parameter to be reconstructed worsen the ill-posedness of the optimization problem, the hybrid method predicts part of them with the NN method, and then finds the other parameters with the CG method. Unlike the inverse analysis given in [2], the newly developed fast forward solver with MME is adopted for the fast calculation of DCPD signals due to a complicated defect.

A. Upgrade of fast scheme for DCPD signal simulation

To treat a defect with complicated boundary with a regular mesh, a new type of element containing different materials inside, i.e., the Multi-Medium Element (Fig. 1), is proposed at first. As there is no local electric charge at the defect surface for DCPD problem, this kind of element is applicable to the FEM simulation of DCPD signals.

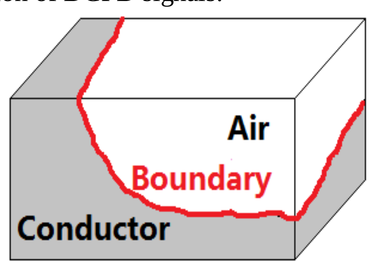

Fig. 1 The multi-media element

As shown in Fig. 1, the MME covers both air and base material (conductor) regions separated by the defect boundary. To efficiently calculate the element coefficient matrix of such an element, an algorithm is developed to divide the gauss points into defect point group and the conductor group at first.

During the inversion analysis with both the NN and the CG methods, a lot of forward simulations have to be conducted. Therefore, a fast forward simulation is very important. In [2], the database type forward solver is introduced for the efficient simulation of DCPD signals of MF. In this work, this fast forward scheme is upgrade further by introducing MME.

The key formulae of the fast forward solver are as follows:

$$\{\varphi_{1f}\} = -[H_{12}K_{22}]\{\varphi_{20} + \varphi_{2f}\}. \tag{1}$$

$$[I + [H_{22}K_{22}]]\{\varphi_{2f}\} = -\{\varphi_{20} + \varphi_{2f}\}. \tag{2}$$

From (1) and (2), once calculated φ_{2f}, perturbation of nodes related to the defect region with (2), φ_{1f} , perturbation of nodes only related to the conductor region, can be solved by (1). In (1) and (2), $[H]$ and $\{\varphi_0\}$ are independent of the flaw geometry, and can be pre-calculated and stored as databases. Thus, large reduction in computer resources can be realized as the number of nodes in the flaw region is much less than that of the whole analysis region.

B. The hybrid inverse strategy

The defect parameters are solved by using optimization method to find a group of optimal parameter values which minimize the following objective function

$$\varepsilon(\mathbf{b}) = \sum_{m=1}^{M} \left\| u_m(\mathbf{b}) - u_m^{\ obs} \right\|^2, \tag{3}$$

where $\mathbf{b}$ is the defect profile parameters, $u_m(\mathbf{b})$ is the simulated potential drop value due to defect $\mathbf{b}$ at the m-th detection point, and u_m^{obs} is the observed signal at the corresponding detection point, M is the total number of signal points.

To solve the defect parameter, the hybrid inverse strategy is proposed by combing the CG optimization algorithm and the artificial NN method. In practice, the location parameters are predicted by using the NN at first. The defect size parameters, then, are reconstructed by the deterministic inversion method with known location information.

The key procedure of the conjugate gradient method [1] is based on the following iteration

$$\mathbf{b}_k = \mathbf{b}_{k-1} + \lambda_k \mathbf{P}_k, \tag{5}$$

where $\mathbf{P}_k$ is the updating direction of k-th iteration, which is chosen as the direction of the conjugate gradient vector of the objective function, λ_k is a step size factor.

On the other hand, a feed forward neural network is adopted to predict the location of the cavity defect. The input of the NN consists of feature parameters of DCPD signals. The outputs are the parameters of the location of defect causing the DCPD signals. The feed forward NN contains a single hidden layer. The training process starts with only one hidden node, and for each training epoch a new node is created. The new input-hidden connections receive random weights and the rest of the weights are obtained based on the training data by using the least square method and the singular value decomposition.

III. VALIDATIONS

Based on the theories given in the previous sections, numerical codes are developed or upgraded for both the forward and the inversion analysis. A DCPD testing system is also used to measure potential drop distribution at test-piece with artificial volumetric defect. All the numerical and the experimental results reveal that the fast forward solver is both suitable to treat a defect of complicated shape and with high efficiency. Fig. 2 gives a comparison of the simulated and measured signals for a cubic aluminum MF block with a cylindrical defect drilled from the bottom of the test-piece with its depth smaller than the thickness of the test-piece. Good agreement can be found even for this practical MF material and for 3D cases. Due to the page limit, the validations of the hybrid inverse analysis scheme will be given in the full paper.

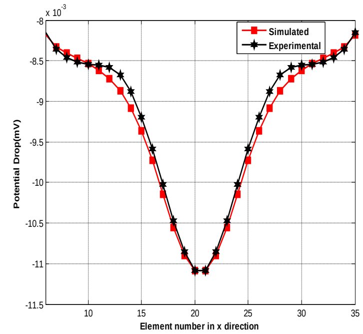

Fig. 2 Experimental validation of the MME method

IV. CONCLUSIONS

In this paper, the database type fast forward scheme is upgraded at first by introducing a multi-medium element. Then, a hybrid method combining the NN and the CG optimization methods is adopted to evaluate the size and position parameters of the defect. The good agreement of the true and the reconstructed defect parameters demonstrated the validity of both the forward and the inversion schemes.

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