Assessment of Partially Conductive Cracks from Eddy Current Non-Destructive Testing Signals using Support Vector Machine

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Abstract. *This paper deals with a three-dimensional non-destructive evaluation of partially conductive cracks from eddy current testing signals. An SUS316L plate specimen containing a crack is non-destructively inspected by the eddy current method using numerical simulations. An extensive database of eddy current response signals is prepared while dimensional parameters of a crack together with its partial conductivity are varied in wide ranges. A Support Vector Machine classification algorithm is employed to solve the electromagnetic inverse problem. The acquired signals are employed for training the algorithm and for testing its performance. It is demonstrated that the Support Vector Machine algorithm is able to properly classify detected defects into proper classes with very high probability even the partial conductivity of a detected crack together with its width are unknown.*

Keywords

Eddy currents, non-destructive evaluation, partially conductive cracks, support vector machine.

1. Introduction

New approaches such as System Health Monitoring and Condition Based Maintenance are nowadays employed for assessment of structural integrity of various components and structures. The modern methods follow three consecutive phases - detection of non-homogeneities, their diagnosis and finally prognosis of their further development. The first two phases are inherently associated with Non-Destructive Evaluation (NDE) of materials. Enhancing NDE methods is therefore very important for reliable assessment of structures.

NDE techniques are based on numerous physical principles and phenomena. Eddy current testing (ECT) is one of the widely utilized electromagnetic NDE methods. ECT works on the basis of an interaction of time-varying electromagnetic field with a conductive body according to the Faraday's electromagnetic induction law. There are many advantages such as high sensitivity for surface breaking defects, high inspection speed, contact-less inspection, versatility, and maturity of numerical means that account for continuously enlarging application area of the ECT, mainly in nuclear, petrochemical and aviation industries [1]. On the other hand, ECT is a relative method and the inverse problem is ill-posed [2]. Therefore, evaluating dimensions of a detected defect from ECT response signals can be quite difficult [3]. ECT instruments provide raw data with limited or absent capability of interpreting quantitatively the data [4]. Typically, evaluation relies on calibrated curves measured on pre-fabricated etalons and on the skills of an operator. Recently, the progress in powerful computers has allowed developing of automated procedures to make decisions. Quite satisfactory results are reported by several groups for automated evaluation of artificial slits [3] and even for several parallel notches [5]. However, evaluation of real cracks, especially stress corrosion cracking (SCC), from ECT response signals remains still very difficult.

SCCs are quite different in comparison with artificial slits or even to other types of real defects. Cross sections of SCC frequently show branched structure and a group of cracks usually occurs in what is known as a colony. The local opening of SCC is usually very small, e.g. tens of micrometers; however, a damaged region itself is much broader. SCC contains many unbroken ligaments both in depth and opening directions, which makes SCC partially conductive [6]. In the case of artificial EDM notches the width is usually considered fixed in the inversion process of ECT signals. However, for cracks with non-zero conductivity the width affects the signal and it has to be considered unknown during reconstruction [7]. It means that the additional variables should be taken into account for evaluation of a detected SCC that considerably increases ill-posedness of the inverse problem [2]. Thus, many unsatisfactory results are reported when the automated procedures originally developed for non-conductive cracks are employed in the evaluation of SCCs. It is stated that one of the possible reasons is lack of sufficient information [3].

Standard ECT inspection is performed in such a way that an ECT response signal is acquired during a two dimensional scanning of an ECT probe over a surface of the tested material. However, only a one-dimensional signal is then employed for the evaluation; a response signal along a detected crack length is extracted from the whole data set. Only three parameters are estimated / the crack surface length, position of its centre and a maximum depth. The crack width and its conductivity are set before the inversion without knowledge of their actual values.

The authors already proposed new approach for the three-dimensional reconstruction of partially conductive cracks such as for example SCCs [8]. The uniqueness of the proposal lays in the utilization of two-dimensional ECT response signals while the estimation of the three-dimensional crack profile is performed. The partial conductivity of a crack and its width as well are considered unknown during the reconstruction. The tabu search stochastic method was used to solve the inverse problem.

Support Vector Machine (SVM) classification algorithm is newly employed to tackle assessment of partially conductive cracks in this paper.

2. Numerical Model

A plate specimen having the electromagnetic parameters of a stainless steel SUS316L is inspected in this study. The specimen has a thickness of $t = 10$ mm, a conductivity of $\sigma = 1.35$ MS·m^{-1} and a relative permeability of $\mu_r = 1$. A single surface breaking crack appears in the plate. It is modelled as a cuboid having different electromagnetic properties from the base material. Configuration of the plate (region Ω_0) with the crack (region Ω_1 is shown in Fig. 1. The crack region Ω_1 ($22 \times 2 \times 10$ mm^3) shown in details in Fig. 2 is uniformly divided into a grid composed of $n_x \times n_y \times n_z$ ($11 \times 5 \times 10$) cells in length, width and depth directions, respectively, defining a possible crack geometry. The dimensions of each cell are $2.0 \times 0.4 \times 1.0$ mm^3.

A new eddy-current probe proposed by the authors is employed for the near-side inspection of the plate [8]. It consists of two circular exciting coils positioned apart from each other and oriented normally regarding the plate surface. The circular coils are connected in series but magnetically opposite to induce uniformly distributed eddy currents in the plate. The exciting coils are supplied from a harmonic source with a frequency of 5 kHz and the current density 1 A·mm^{-2}. ECT response signal is detected by a small circular coil located in the centre between the exciting coils to gain high sensitivity as the direct coupling between the exciting coils and the detector is minimal at this position. The configuration of the new probe is shown in Fig. 3. Dimensions of the detecting coil are as follows: an inner diameter of 1.2 mm, an outer diameter of 3.2 mm and a winding height of 0.8 mm. The detecting coil is oriented along the z-axis according to the coordinate system shown in Fig. 3.

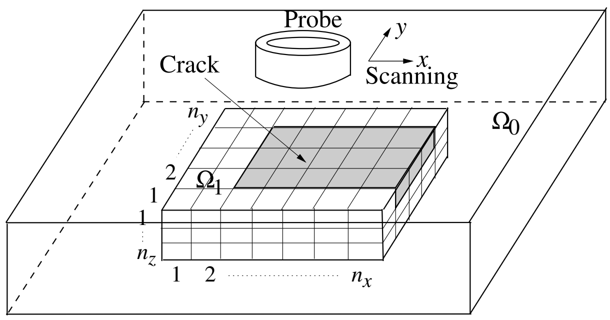

Fig. 1: Configuration of plate specimen with crack region.

Two-dimensional scanning, the so called C-scan, is performed over the cracked surface with a lift-off of 1 mm. The real and imaginary parts of the induced voltage in the detecting coil are sensed and recorded during the inspection.

The fast-forward FEM-BEM analysis solver using database [9] is adopted here for the ECT response signals simulation. Actually, a version of the database algorithm upgraded by the authors in previous works [5] for the computation of the ECT signals due to multiple cracks is used in this paper. The database is designed for a three-dimensional defect region and not as usually for a two-dimensional one where a crack width is

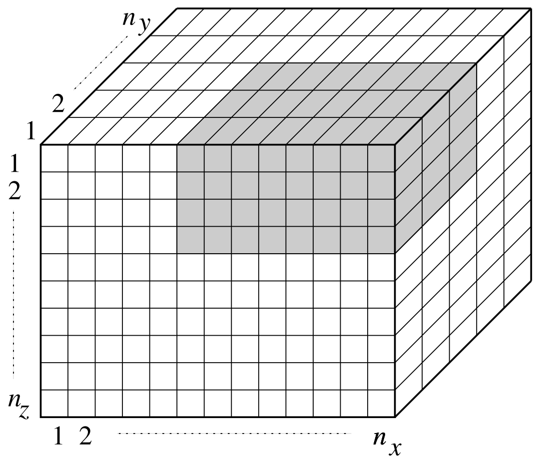

Fig. 2: Crack model.

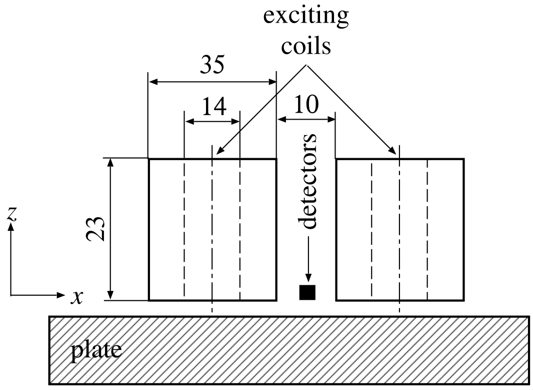

Fig. 3: ECT probe configuration.

considered fixed. Thus, the ECT response signals can be simulated also for partially conductive cracks with variable width using the same database generated in advance. The area of the simulated two-dimensional ECT signals has surface dimensions of 100×28 mm^2. The number of scanning points in the two directions is 50 and 70, respectively.

In total, 6050 scenarios are simulated, while the crack parameters are changed as follows:

- length: from 2 to 22 mm with a step of 2 mm,
- width: from 0.4 to 2.0 mm with a step of 0.4 mm,
- depth: from 0 to 10 mm with a step of 1 mm,
- partial conductivity: from 0 to 10 % of the base material conductivity.

3. Support Vector Machine

Support Vector Machine (SVM) is related to the supervised learning methods that analyse data and recognize patterns. It is a non-probabilistic binary linear model based classifier. The training algorithm constructs a model that represents patterns as points in the vector space. Such mapped patterns of the separate classes are divided by a gap that is as wide as possible [10]. Development of the classification system includes data separation into training and testing sets. Each instance in the training set contains features of the observed data and the class labels. The training set consists of the instance - label pairs (x_i, y_i), $i = 1, 2, ..., l$, where $x_i \in R^n$ and $y = \{1, -1\}^l$. The SVM requires solution of the optimization problem [11]:

$$\min_{w,b,\xi} \left\{ \frac{1}{2} w^T w + c \sum_{i=1}^{l} \right\} \xi_i, \tag{1}$$

with subject to:

$$y_i \left(w^T \phi(x_i) + b \right) \geq 1 - \xi_i, \xi_i \geq 0, \tag{2}$$

where $\phi(x_i)$ maps x_i into a higher dimensional space and $C > 0$ is the regularization parameter. Due to possibly high dimensionality of the vector variable ωone usually solve the following dual problem defined as:

$$\min_{\alpha} \left\{ \frac{1}{2} \alpha^T Q \alpha - e^T \alpha \right\}, \tag{3}$$

subject to:

$$y^T \alpha = 0, 0 \leq \alpha_i \leq C, \tag{4}$$

where $i = 1, 2, ..., l$ and $e = [1, 1, ..., 1]^T$ is the vector of all ones of the length l, Q is an l by l positive semidefinite matrix, $Q_{ij} \equiv y_i y_j K(x_i, y_j)$ and $K(x_i, x_j) \equiv \phi(x_i)^T \phi(x_j)$ are the kernel functions [10], [11].

As soon as the problem Eq. (1) is solved, the optimal w satisfies the term Eq. (3) and the decision function is as follows:

$$\mathrm{sgn} \left(w^T \phi(x + b) \right) = \mathrm{sgn} \left(\sum_{i=1}^{l} y_i \alpha_i K(x_i, x) + b \right), \tag{5}$$

after this step, $y_i \alpha_i \forall i, b$ label names support vectors and other information such as kernel parameters are stored in the model [11].

There are four basic kernel functions: linear, polynomial, radial basic function (RBF) and sigmoidal function. Each of the kernels has one or more parameters to be set depending on the particular type. The most frequently used kernel function - RBF is defined as [11]:

$$K(x_i, y_j) = \exp\left(-\gamma \parallel x_i - y_j \parallel^2 \right), \gamma > 0. \tag{6}$$

The quality of SVM models depends on the proper setting (tuning) of SVM hyper-parameters process called SVM model selection. This is a challenging problem due to the inclusion of kernels in the SVM. On the one hand, SVMs can implement a variety of representations via the choice of the kernel. On the other hand, kernel specification defines a similarity metric (data encoding) in the input space, which complicates model selection [12].

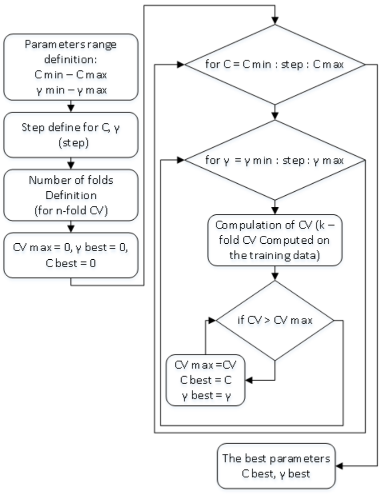

Fig. 4: Grid search algorithm.

According to [12], SVM model selection depends in general on two parameters:

- parameters controlling the "margin" size,
- model parameterization, which is the choice of kernel type and its complexity parameters.

Successful tuning of SVM parameters requires a conceptual understanding of their role and their effect on the generalization ability. It is important to make a distinction between SVM parameters controlling the margin size and those controlling the model flexibility. For example, the margin size is controlled by parameter C and the model flexibility is controlled by the kernel parameters described above. As for regression problems, the width of the insensitive zone (inversely related to margin size) is controlled by the value of ϵ, and the model flexibility can be controlled by the kernel complexity parameter and/or the regularization parameter C.

Figure 4 shows a Grid Search approach belonging to the exhaustive approach for model selection, and also optimized parameter tuning using an evolutionary algorithm. The grid search is one of the widely used approaches for model parameter selection.

4. Reconstruction of Partially Conductive Cracks

A design of reconstruction scheme and particular results of the automatic reconstruction of a detected defect are presented in this section. The process of developing the reconstruction algorithm can be summarized as follows. The large database of the eddy current response signals is built at first according to the explanation provided in section 2. The calculated response signals are then divided into the training and the testing sets. The signals from the training sets are read by the algorithm to train the classifier. After the SVM is trained, the signals from the test sets are used for validation. The later signals are classified into defined classes according to the crack?s dimensions and its partial conductivity to provide results of the three-dimensional crack reconstruction.

The other possibility on the contrary to the deterministic method of the SVM parameters setting is to exploit an evolution optimization techniques usually based on stochastic processes. These methods are able to find solutions that can be very close to the optimal ones even on the multimodal function with many local extremes [10]. In the experiment, C-SVM formulation with RBF kernel function is used. This formulation of SVM requires setting of two cost parameters:

- parameter C which has the value between 2^{-5} and 2^{20},
- parameter γ which is between 2^{-20} and 2^{5}.

The search method for selecting near - optimal parameters is called the grid search. This method exhaustively calculates K-fold Cross-Validation (CV) accuracy for every combination from the defined region of parameters C and γ. For instance, if performing a coarse search of region between 2^{-5} and 2^{20} for the parameter C, one could choose to try every cost parameter 2^m for $m = -5, -4, ..., 0, ..., 19, 20$. For each of these C parameters, one try every γ at the value 2^m for $m = -20, -19, ..., 0, ..., 4, 5$. This search requires running SVM training for 676 different parameters combinations. This technique is very time consuming even for searching of two model parameters [10].

Table 1 provides the distribution of a number of signals to the training and the testing sets of SVM models including parameters obtained using grid search algorithms, which are used to train the SVM models. Finally, the accuracy of training SVM models and testing signals are shown in Tab. 1, too. The best results are received for SVM model 98.0727 %. Only two from the 550 test signals are not correctly classified into proper classes. The signal of a crack with following parameters: length 20 mm, width 2 mm, depth 9 mm and

Tab. 1: Results of SVM.

Training signals	Testing signals	C	γ	Training accuracy[%]	Testing accuracy[%]
6050	550	19.7	5.0	98.3140	87.4545
6050	550	19.9	4.3	98.1818	87.4545
5500	550	19.7	5.0	98.0727	99.6364
5500	550	19.9	4.3	98.0	99.6364

partial conductivity 6 % of the base material conductivity is classified as a crack with parameters: length 20 mm, width 2 mm, depth 10 mm and partial conductivity 6 % of the base material conductivity. It means that there is a difference of crack depth identification of 1 mm (10 %). The same misclassification appeared for the crack with the same dimensional parameters and partial conductivity of 5 % of the base material conductivity. It can be stated that the SVM algorithm classified the testing signals into proper classes with very high accuracy.

5. Conclusion

The paper dealt with a three-dimensional reconstruction of partially conductive cracks from eddy current non-destructive testing signals. A large database of the eddy current response signals was developed using numerical simulations. The response signals were calculated for a wide variety of crack dimensional parameters and its partial conductivity. A part of the calculated signals was used to train Support Vector Machine algorithm employed for automatic assessment of a detected crack. The crack width and its partial conductivity were taken as additional variables in the inversion process. The algorithm was tested on the other part of signals. It was revealed that the Support Vector Machine classification algorithm can classify the signals into proper classes with very high preciseness. This method has a very high and still unlocked potential in the field of non-destructive evaluation.

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