AN AI APPROACH TO THE EDDY CURRENT DEFECT CHARACTERIZATION PROBLEM

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INTRODUCTION

Conventional eddy current NDT methods rely for their operation on the interaction of quasi-static electromagnetic fields with flaws in the specimen under test. The physics of such interactions are described completely by a parabolic diffusion equation

$$\nabla \times \left( \frac{1}{\mu} \nabla \times \mathbf{A} \right) = -\sigma \frac{\partial \mathbf{A}}{\partial t} + \mathbf{J}_s$$  \hspace{1cm} (1)

derived from the quasi-static form of Maxwell’s equations. This precludes the use of methods such as holography and tomography in the analysis of data from eddy current probes [1]. Ideally, one would desire an analytical closed form solution of equation (1) in terms of the material parameters $\mu(\mathbf{r})$ and $\sigma(\mathbf{r})$, so that one has a direct method for solving the inverse problem or imaging problem. The nature of the defect characterization problem in eddy current NDT and the difficulties involved in the analytical modeling of realistic test geometries are described at length in [2,3]. Simulation of nonlinear, practical problems with arbitrary defect shapes are generally done using numerical techniques such as the finite difference and finite element methods. However, the major drawback of numerical models is lack of a closed form solution, which renders them inadequate for directly solving the inverse problem. This paper presents a new approach to the general inverse problem in NDT of defect imaging, that uses the finite element model iteratively for estimating the test specimen parameters $\{g\}$ as shown in Figure 1.
Fig. 1. Algorithm for the parameter estimation problem.

The method, based on artificial intelligence techniques, reduces the general inverse problem to a tree or state space search. One of the commonly used problem solving techniques in artificial intelligence is the method of heuristic search where one searches for the optimal solution in a space of all potential solutions. The method typically consists of two steps:

i) State space representation of problem
ii) Search procedure

In order to understand the formulation and implementation of the algorithm, the following definitions are useful.

DEFINITIONS AND NOTATIONS

A state or a node is defined as a possible configuration of relevant parameters in the problem domain. The set $S$ of all possible states of the problem is called the problem state space. A state transformation operator $O$ is a rule which transforms a node 'a' in $S$ to a node 'b' in $S$. 'b' is called the successor of 'a'. The generation of all successors of a node is referred to as the expansion of the node. The starting state of the system is called the root node or initial node and the goal node is a node that satisfies some prescribed termination criteria. The tree representation of the problem state space is given by the quadruple $[S,T,I,G]$ where $S$ is the problem state space, $T$ is the set of state transformation operators, $I$ is the set of initial nodes and $G$ is the set of goal nodes. The problem solution is then obtained using a tree search procedure. In most problems, however, the state space to be searched is explosively large and one has to use heuristics, defined as a strategy that reduces the search effort. The following two sections describe the tree-representation of the eddy current imaging problem and the search procedure used.

PROBLEM REPRESENTATION

The tree representation of a problem state space is completely specified by identifying precisely the four sets in the quadruple defined in the previous section. Heuristic information about the problem can also be built into the general scheme.
Problem State Space

A typical test specimen is a three dimensional object but this paper considers an axisymmetric test geometry shown in Figure 2 where an eddy current probe moves inside a hollow tube with axisymmetric defects in the tube wall. Discretizing the test object by a two dimensional matrix of rectangular cells, the states of the problem are identified by matrices of the form

\[
\mathbf{s} = \begin{bmatrix}
p_{11} & p_{12} & \cdots & p_{1n} \\
p_{21} & p_{22} & \cdots & p_{2n} \\
p_{mn} & p_{m2} & \cdots & p_{mn}
\end{bmatrix}
\]

where the row and column indices of an element select a cell in the object and the value of the element is either 0, indicating presence of a flaw, or 1 indicating no flaw in the cell. The state \( \mathbf{s} \), then represents the discrete spatial distribution of material properties in the test specimen. As shown in Figure 3, the discretization of the tube wall is not uniform but conforms to the finite element mesh that models the problem.

Fig. 2. Axisymmetric eddy current NDT geometry.

Fig. 3. Two dimensional discretization of tube wall corresponding to the mesh used in the finite element model.
State Transformation Operators

Since the search space for a discretization of \( m=n=l=10 \) consists of \( 2^{100} \) states, it is required to introduce heuristics to constrain the search to a reduced subspace. These constraints can be incorporated into the state transformation rules so as to limit the expansion of a node to a select few successors. In the first constraint the defect boundary, defined by a two dimensional sequence of edges as explained in Figure 4, is considered to be a two dimensional discrete time Markov process indexed by the depth into the material in units of cells. The transition probability matrices characterizing the Markov process is chosen to allow only smoothly varying boundaries and transitions leading to sharply varying boundary sequences are prohibited. Figure 5 contains a very simple choice of transition probability matrices. The second constraint is based on the assumption that the crack/defect grows only narrower with depth. These constraints result in a considerable reduction of the search space by defining \( T \) such that the fanout factor for a node expansion is 6 as seen in Figure 6.

Fig. 4. Defect boundary, defined by sequences of edges, modelled by a Markov process.

\[
P_{12} = \frac{1}{3} \begin{bmatrix} 1 & 1 & 1 \end{bmatrix}
\]

\[
P_{23} = \frac{1}{3} \begin{bmatrix} 1 & 1 & 1 & 0 & 0 \\ 0 & 1 & 1 & 1 & 0 \\ 0 & 0 & 1 & 1 & 1 \end{bmatrix}
\]

\[
P_{34} = \frac{1}{3} \begin{bmatrix} 1 & 1 & 1 & 0 & 0 & 0 \\ 0 & 1 & 1 & 1 & 0 & 0 \\ 0 & 0 & 1 & 1 & 1 & 0 \\ 0 & 0 & 0 & 1 & 1 & 1 \\
\end{bmatrix}
\]

Fig. 5. Transition probability matrices.
Initial Node

Restricting the class of defects to surface breaking cracks, the initial node is defined by the spatial extent of the flaw at the surface. It is represented by a two dimensional, unit length Markov chain \( \{x_1^L, x_3^R\} \)

Fig. 6. Expansion of a node into its successors.

corresponding to the left and right edges of the surface opening. The start node is determined using characteristic features in the experimental signal. For instance, in Figures 7 the phase plots of the eddy current probe signal for three defect widths, exhibit a discontinuity close to edges of the defect and is used for estimating the initial node.

Fig. 7. Eddy current phase signal for three different defect widths.
Goal Node

The goal node of the problem is defined by the two dimensional depth profile generated by the left and right edge sequences such that the corresponding defect produces a signal at the surface that is 'closest' to the experimentally measured signal.

SEARCH PROCEDURE

A simple A* type algorithm [4] is used to search for the goal node. The search is conducted in two phases, namely the node generation phase and the node evaluation phase. The first few steps of the basic search procedure are given below.

1. Define \( S_1 = \{x_1^L, x_1^R\} \) where \( x_1^L \) and \( x_1^R \) indicate the unit length, left and right edge sequences. The corresponding defect obtained by labeling all the cells in the layer \( K=1 \) and in between \( x_1^L \) and \( x_1^R \) as belonging to defect (air) is input to the FE model. The node \( S_1 \) is evaluated by computing \( e(S_1) = \text{distance} \) between model output and input signal. If \( S_1 \) is not goal node store \( S_1 \) and \( e(S_1) \).

2. Expand node \( S_1 \). Define

\[
S_{2}^{k} = \{x_{2,i}^L, x_{2,j}^R\} , \{x_1^L, x_1^R\}
\]

\( i=1,2,3; \quad j=1,...,i; \quad k=1,2,...,6 \)

Compute \( e(S_{2}^{k}) \), \( k=1,2,...,6 \).

Check for goal node.

3. Select the most promising (smallest \( e \) value) unexpanded node and go to 2.

Some of the evaluation functions used in the algorithm were the \( \ell_2 \) norm and the \( \ell_\infty \) norm.

RESULTS

The method was first tested on defects simulated using the FE model. Simple defects input to the system and the results of the algorithm are shown in Figure 8. The complete tree expansion with the cost of each node using \( \ell_2 \) and \( \ell_\infty \) norms is shown for the simple rectangular defect. A more complex shaped defect input to the system and the corresponding result is seen in Figure 9. Results of implementing the algorithm on some experimental signals from axisymmetric rectangular defects are given in Figure 10.

CONCLUSIONS

Results obtained so far do indicate the potential of the method as a possible imaging tool. The approach used is very general and can be applied to variety of problems such as eddy current NDT or ultrasonic NDT by employing the appropriate FE model. The imaging procedure depends on extensive use of the numerical model, and is computationally intensive, but when a forward problem is best described by a numerical model the approach presented here seems to be the only method for solving the inverse problem.
Fig. 8. Eddy current simulation results on some simple defects.

Fig. 9. Eddy current simulation results on a complex defect profile.
Fig. 10. Results of implementation on experimental eddy current signals from three rectangular defects.

REFERENCES


