Geometry Parameters Estimation of Defects in Multi-layered Structures Based on Eddy Current Nondestructive Testing Technique with Bayesian Networks

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Abstract

To determine the geometry parameters of defects in multi-layered structures is one of the principal challenges in the research field of eddy current nondestructive testing. For buried defects the direct observation of the values of these geometry parameters is practically impossible. So it is necessary to estimate such values. Bayesian networks (BNs) have been proved to be a potentially useful alternative in defect geometry parameters estimation. These geometry parameters are derived from the conditional probability distributions (CPDs) estimation in BNs with experimental data. This paper describes how a novel algorithm based on BNs can be applied to successfully estimate CPDs of defect geometry parameters. In scanning inspection, the eddy current signals were preprocessed for noise elimination using wavelet packet analysis method. Then, BNs were applied to a realistic multidimensional parameters estimation problem of defect dimensioning. Finally, the estimation results were analyzed. Measurement uncertainty was generally characterized from CPDs of defect geometry parameters. The feasibility of the presented BNs has been validated.

Keywords: Eddy current nondestructive testing, Inverse problems, Defect geometry parameters estimation, Bayesian networks

1. Introduction

As is known to all, the detection of internal defects in multi-layered structures, as well as the estimation of their geometry parameters is important in a range of technological applications, such as maintaining the integrity of structures, enhancing the security of aging aircraft and assuring the quality of products[1]. Defects are generally formed into multi-layered structures by residual stress or physical or metallurgical process, and they can increase in number and dimension in time because of fatigue and consumption, causing damage and sometimes sudden breakdown. For this reason, it is emergent to develop and implement the disposal procedures capable of giving us information about the geometry parameters reached by the defect, through inspection of external surface of the body. Eddy current nondestructive testing (ECNDT) is relatively rapid and has advantages of high sensitivity, non-contact, low cost, easy realization automated on-line testing and is one of the rigorous, physics-based phenomenology for identifying micro hidden defects.

In ECNDT, information concerning defect dimension and relative position can be retrieved by inversion of the measured data representing changes in impedance of the coil as it scans over the specimen. To determine geometry parameters of defects in the multi-layered structures is a very difficult inverse problem since it here is ill-posed and nonlinear. Although many researchers have presented several computational methods, the ECNDT inverse problem in multi-layered structures still poses a major challenge and remains to be dealt with[2, 3]. Therefore, a general framework for evaluation of eddy current (EC) signals is very desirable, which can not only rapidly but accurately work out the geometry parameters of defects in multi-layered structures.

This paper presents a Bayesian networks (BNs) based approach for geometry parameters estimation of defects in the multi-layered structures. BNs are a powerful method for knowledge representation and reasoning under uncertainty[4]. In ECNDT, defect geometry parameters estimation procedures can benefit from these special properties of BNs, making them more powerful and applicable to handle the real uncertainty measures, which can lead to more general model and sufficiently accurate results. In this paper, BNs were applied to estimate realistic multidimensional defect geometry parameters by probability inference. Experimental results show that the proposed method keeps higher estimation accuracy than previous methods.

The remainder of the paper is organized as follows. Section 2 briefly surveys signals de-nosing using wavelet packet analysis (WPA) method. Section 3 reviews the principle of BNs which can be used to estimate defect geometry parameters. Section 4 presents experimental results. Finally, Section 5 contains conclusions.

2. Signal De-nosing

In ECNDT, the output signals may be corrupted by noise and other artificial signals, arising from lift-off, edge effects, high-frequency and white noise, probe angle variations, etc., resulting in unreliable detection and inaccurate characterization of defect dimension. In order to remove the influence of noise and extract the amplitude of the main components from the measurements, a number of preprocessing steps are required before defect parameters estimation is possible.

WPA has proved its great capabilities in decomposing, de-noising, and signal analysis which makes the analysis of non-stationary signals achievable as well as detecting transient feature components, since wavelet can impart time and frequency structures. The wavelet packet de-noising procedure involves four steps:

1) Decomposition: For a given wavelet, compute the wavelet packet decomposition of signal $f(t)$ at level m.

2) Computation of the best tree: For a given entropy, compute the optimal wavelet packet tree. Of course, this step is optional.

3) Threshold setting of wavelet packet coefficients: For each packet (except for the approximation), select a threshold and apply it to coefficients.

4) Reconstruction: Compute wavelet packet reconstruction based on the original approximation coefficients at level m and the modified coefficients.

3. Bayesian Networks

BNs are graphical models for probabilistic relationships among a set of variables[4]. Over the last decade, BNs have become a popular representation for encoding uncertain expert knowledge in expert systems. More recently, researchers have developed methods for learning BNs from data. The techniques that have been developed are new and still evolving, but they have been shown to be remarkably effective for data analysis problems.

3.1 Bayesian networks model

BNs are directed acyclic graphs (DAGs) that allow for efficient and effective representation of the joint probability distributions over a set of random variables. Let $\boldsymbol{V}=\{V_1, V_2, \ldots, V_N\}$ be a set of random variables, with each variable V_i taking values in some finite domain $Dom\{ V_i \}$. BNs over $\boldsymbol{V}$ is a pair $(\boldsymbol{G}, \boldsymbol{\theta})$ that represents sets of distributions over the joint space of $\boldsymbol{V}$. $\boldsymbol{G}$ is a set of DAGs, whose nodes correspond to the random variables in $\boldsymbol{V}$ and whose structure encodes conditional independence properties about the joint distributions. $\boldsymbol{\theta}$ is a set of parameters which quantify the networks by specifying the conditional probability distributions (CPDs). Given the independences encoded in the networks, the joint distributions can be reconstructed by simply multiplying these local conditional distributions.

$$P(\boldsymbol{V}) = \prod_{i=1}^{N} P(V_i \mid V_1, V_2, \ldots, V_{i-1}) \tag{1}$$

For each variable V_i, let the parents of V_i denoted by $Par_i \subseteq \{V_1, V_2, \ldots, V_{i\text{-}1}\}$ be a set of variables that render V_i and $\{V_1, V_2, \ldots, V_{i\text{-}1}\}$ independent, that is

$$P(V_i \mid V_1, V_2, \ldots, V_{i-1}) = P(V_i \mid Par_i) \tag{2}$$

Note that Par_i does not need to include all elements of $\{V_1, V_2, \ldots, V_{i\text{-}1}\}$ which indicate conditional independence between those variables not included in Par_i and V_i given that the variables in Par_i are known. The dependencies between the variables are often depicted as DAGs with directed arcs from the members of Par_i (the parents) to V_i (the child). BNs describe the dependencies between variables if they depict causal relationships between variables. So, BNs are commonly used as a representation of the knowledge of domain experts. Experts both define the structure of the BNs and the local conditional probabilities. In this paper we use these ideas in context with continuous variables and dependencies, where the probability distributions of all continuous variables are multidimensional Gaussian ones.

3.2 Learning Bayesian networks

The learning process is how to refine the structure and local probability distributions of the BNs given data[5]. The results are a set of techniques for data analysis that combine prior knowledge with data to produce improved knowledge. In a real application, the domain knowledge base on specified set of rules which can be used to create BNs structure on a case by case basis. It is clear that the models created in this way are strictly based on the special physical process. During the defect geometry parameters estimation based on ECNDT, the BNs structure can be constructed using the knowledge of the relationship of the probe response signals and the defect dimension. In this section, we only consider the problem using data to update the probabilities of a given BNs structure.

We assume that the goal of learning in this case is to find the maximum likelihood estimates (MLEs) of the parameters of each CPDs, i.e., the parameters vary to maximize the likelihood of the training data, which contains M cases (assumed to be independent). The normalized log-likelihood of the training set $\boldsymbol{D}=\{D_1, D_2, \ldots, D_M\}$ is a sum of terms, one for each node:

$$L = \frac{1}{M}\log\prod_{m=1}^{M} P(D_m \mid G) = \frac{1}{M}\sum_{i=1}^{n}\sum_{m=1}^{M}\log P(V_i \mid Par_i, D_m) \tag{3}$$

where Par_i are the parents of V_i. The log-likelihood scoring function can be decomposed according to the structure of the graph, and hence the contribution to the log-likelihood of each node can be maximized independently.

All that remains are to estimate the parameters of each type of CPDs given its local data $\{D_M (V_i, Par_i)\}$. A large number of techniques using supervised learning methods can be applied at this point. For the Gaussian nodes, the MLEs of the mean and covariance are the sample mean and covariance, and the MLEs of the weight matrix are the least squares solution to the normal equations.

3.3 Inference in Bayesian networks

Once we have constructed BNs (from prior knowledge, data, or their combination), we usually need to determine various probabilities of interested nodes from the model. In defect parameters estimation, we want to know the defect parameter values and their CPDs given the EC inspection signals. These probability distributions are not stored directly in the model, and hence need to be computed. In general, the computation of probability distributions of interest is known as probabilistic inference[5].

Various inference algorithms can be used to compute the marginal CPDs for each unobserved node given information of a set of observed nodes. Recent algorithms developed for inference in BNs, such as the junction trees by Jensen, provide a more efficient solution to propagation in DAGs. The junction tree method is a new iterative algorithm that efficiently combines dynamic discretization with robust propagation algorithms to perform inference in a hybrid BNs[6].

A junction tree representing BNs ($\boldsymbol{G}$, $\boldsymbol{\theta}$) is constructed by moralization and triangulation of $\boldsymbol{G}$. In the junction tree, the basic nodes are represented as cliques which are maximal complete subgraphs of the triangulated graphs. The cliques are connected by separators which are also called junction tree property holds. The separator $S= C_i \cap C_j$ is a path between two cliques C_i and C_j and subset of C_i and C_j. Each variable and its parents in the junction tree are contained in at least one clique.

Every CPDs of the original BNs $P(V_i| Par_i)$ are associated with a clique such that the domain of the distributions is the subset of the clique domain. The notation $Dom(\psi)$ represents the domain of a potential ψ. The set of distributions Ψ_C associated with a clique C are combined to form the initial clique potential ψ_C :

$$\psi_C = \prod_{\psi \in \Psi_C} \psi \tag{4}$$

Inference in junction tree based architectures is performed by passing messages between the adjacent cliques. At the beginning of messages passing, each separator is initially empty. During inference each separator is updated to hold each of the potentials passed over the separator. The clique potentials are, on the other hand, left unchanged. When evidence is absorbed from C_j to C_i, the potential ψ^*_S passed over the separator S connecting C_i and C_j is calculated as:

$$\psi^*_S = \sum_{C_j \backslash S} \psi_{C_j} \prod_{S' \in ne(C_j) \backslash \{S\}} \psi_{S'} \tag{5}$$

where $ne(C_j)$ is the set of neighboring separators of a clique C_j.

After a full round of message passing, the joint probability distributions (up to the same normalization constant) of any clique C_i in the junction tree can be computed as the combination of the clique potential and all the received potentials associated with neighboring separators:

$$\psi^*_{C_i} = \psi_{C_i} \prod_{S \in ne(C_j)} \psi_S \tag{6}$$

From a consistent junction tree, the posterior marginal CPDs of a variable X and the evidence

E can be computed from any clique or separator potential ψ containing X by eliminating all variables in $Dom(\psi)$ except X:

$$P(X,E)=\sum_{Y\in Dom(\psi)\backslash\{X\}}\psi \tag{7}$$

The marginal CPDs of X given E are computed by normalization (note that $P(E)=\sum_X P(X,E)$).

5. Experimental Results

To verify the feasibility of the proposed method for defect geometry parameters estimation, comparative experiments were carried out. The EC inspection is treated as a static stochastic process with uncertainty. We will construct an activity system of defect geometry parameters estimation using BNs, represented as a simple graphical model. The digital signals were processed to remove the influence of noise. After that, the resulting signals and corresponding defect geometry parameters constituted the labeled data which were used to train the BNs. After the properly training, the results would be a generative model suitable for using in the ECNDT system, which was able to estimate defect parameters from the EC signals in real time circumstances.

During the experiments, the coil parameters are: inner radius r_1=3.0 mm, outer radius r_2=5.11 mm, length l=20.7 mm, frequency f=0.2 kHz, lift-off 0.5 mm. The skin depth $\delta=1/\sqrt{\pi f\mu\sigma}$ is equal to about 8.28 mm and indicates promising robustness of inspection inner defects in the multi-layered structures. The probe coils were scanned over the upper side of the multi-layered structures in the plate length direction.

Two groups of experiments have been carried out. Firstly, we considered a simple defect geometry parameters estimation problem that only one parameter of defects in the multi-layered structures needed to be determined. The first experimental specimen (specimen #1) is shown schematically in Fig. 1. It is composed of three layers of aluminum with a total thickness of 7.5 mm. The thickness of each layer is 2.5 mm. There are 7 holes with varying diameter in the middle plate. A major goal is to extend the utilization of the BNs for the defect diameter estimation. Each plate has electrical conductivity σ=18.5 MS/m, magnetic permeability $\mu=\mu_0=4\pi\times10^{-7}$ H/m, length l=440 mm and width w=80.0 mm. The hole parameters are: electrical conductivity σ=0 S/m, magnetic permeability $\mu_0=4\pi\times10^{-7}$ H/m, diameter 1, 2, 3, 4, 5, 6 and 7 mm and depth 2.5 mm.

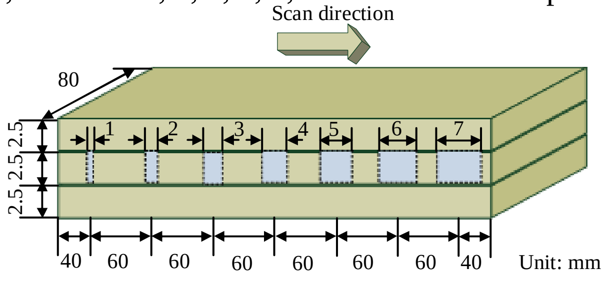

Fig.1 The sketch of defects of varying diameter in multi-layered structures (specimen #1).

In the experiment, the random variables are the defect diameter X and the probe response signals Z. From the general knowledge of the ECNDT, the probe response signals vary with the defect diameter. When the assumption of the other factor's influence seems to be very small, it is clear that the link between X and Z will lead to the BNs given in Fig. 2. In this case, the distributions of X and Z are assumed as multidimensional Gaussian ones with unknown mean and variance (classical assumptions).

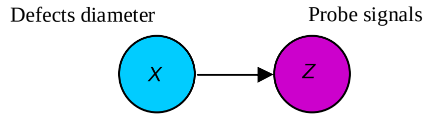

Fig. 2 The BNs used in example 1 (specimen #1).

Then, we trained this model using real research data. Seven types of signals corresponding to seven types of defects were obtained from the inspection. A total of 210 complex valued EC data vectors (each type of defect having 30 records) containing signals corresponding to different types of defects were available for the test. Initially, the data set was de-noised by the WPA method with Shannon entropy. Then, the resulting signals and corresponding defect geometry parameters constituted the labeled data which was sent to train the BNs.

Once built the model, we could use it to predict the defect diameters when the inspection signals were available. The main step was to enter each of inspection signals as evidence and calculate the marginal CPDs of the node X. In fact, since the remaining variables (those not known) are random, the most informative item we can get is its marginal CPDs, and this is what the BNs methodology supplies. However, normally one is interested in giving point predictions and/or probability intervals for predictions. To this end, we can use the mean of the unknown node X as predictions and the marginal CPDs for probability intervals. In this paper, the performance of estimation was evaluated with the bootstrap cross-validation method. The estimated results using BNs are shown in Table 1. Furthermore, the estimated results obtained from BNs are also compared with those of the least square regression method shown in Table 2.

Table 1

Defect geometry parameters Estimation using BNs (specimen #1)

	Group 1	Group 2	Group 3	Group 4	Group 5	Group 6	Group 7
True diameter (mm)	1	2	3	4	5	6	7
Estimated diameter (mm)	1.084	2.139	3.183	3.806	4.732	6.367	7.410
variance of estimated diameter	0.0179	0.0188	0.0139	0.0167	0.0188	0.0197	0.159
Diameter error (%)	8.40	6.95	6.10	-4.85	-5.36	6.12	5.86

Table 2

Defect geometry parameters Estimation using the least square regression method (specimen #1)

	Group 1	Group 2	Group 3	Group 4	Group 5	Group 6	Group 7
True diameter (mm)	1	2	3	4	5	6	7
Estimated diameter (mm)	1.236	2.321	2.508	4.639	5.578	5.112	7.997
Diameter error (%)	23.60	16.05	-16.40	15.98	11.56	-14.80	14.24

Secondly, a more complex example was considered. The signals were collected from multi-layer samples with defects varying diameter and depth were analyzed. Fig. 3 illustrates the second experimental specimen with 5 holes in the middle layer of the three-layered conductive structures (specimen #2). The specimen consists of three layers of aluminum with a total thickness of 10 mm (2.5, 5, 2.5 mm), electrical conductivity σ=18.5 MS/m, magnetic permeability $\mu=\mu_0=4\pi\times10^{-7}$ H/m, length l=420 mm and width w=80 mm. The holes parameters: σ=0 S/m, $\mu_0=4\pi\times10^{-7}$H/m, diameter and depth are (1, 2.5), (2, 3.5), (3, 4.5), (4, 5.5) and (5, 6.5) mm respectively.

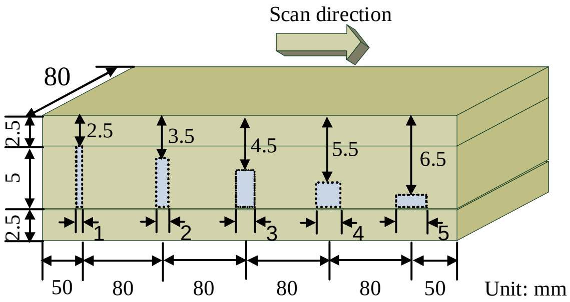

Fig. 3 The sketch of defects of varying diameter and depth in multi-layered structures (specimen #2).

In this example, the random variables are the defect diameter *X*, defect depth *Y* and the probe response signals *Z*. The defect diameter and depth are two independent factors resulting in the probe signals. Using this special relationship, we can obtain the BNs structure given in Fig. 4. In the graph depicted in Fig. 4, node *X* and node *Y* are linked to node *Z* by an arc respectively. Like the first example, the distributions of *X*, *Y* and *Z* are also assumed as multidimensional Gaussian with unknown mean and variance.

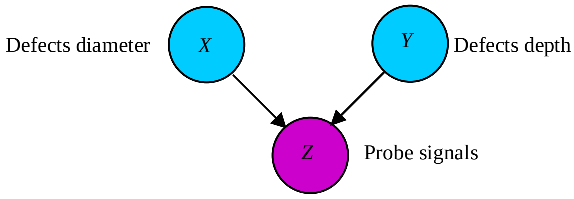

Fig. 4 The BNs used in example 2 (specimen #2).

In the experiment, a dataset with 150 records was acquired during the scanning. The dataset contains EC signals from samples of 5 types of defects (each type of defect having 30 records). As the former experiments suggested, the same procedures were carried out. The estimated results using BNs and the least square regression method are shown in Table 3 and Table 4 respectively.

Table 3

Defect geometry parameters Estimation using BNs (specimen #2)

	Group 1	Group 2	Group 3	Group 4	Group 5
True diameter (mm)	1	2	3	4	5
True depth (mm)	2.5	3.5	4.5	5.5	6.5
Estimated diameter (mm)	1.102	2.221	2.805	3.689	5.449
Estimated depth (mm)	2.679	3.799	4.785	5.079	6.869
variance of estimated diameter	0.0196	0.0160	0.0191	0.0176	0.0138
variance of estimated depth	0.0239	0.0163	0.0209	0.0167	0.0129
Diameter error (%)	10.20	11.05	-6.50	-7.78	8.98
Depth error (%)	7.16	8.54	6.33	-7.65	5.68

It can be seen from the results above that the BNs method has higher precision and robustness than the least square regression method. BNs can combine the knowledge of defect geometry parameters estimation based on ECNDT with the reasoning under uncertainty in AI, which provide not only the predicted geometry values of the defects in the multi-layered structures, but also the probability distributions of these values. The least square regression method proved limited in application because of its less accurate model that was impossible in practice. These results indicate the presented method based on BNs can successfully discriminate between various types of EC signals.

Table 4

Defect geometry parameters Estimation using the least square regression method (specimen #2)

	Group 1	Group 2	Group 3	Group 4	Group 5
True diameter (mm)	1	2	3	4	5
True depth (mm)	2.5	3.5	4.5	5.5	6.5
Estimated diameter (mm)	1.289	2.410	3.459	3.435	4.249
Estimated depth (mm)	2.979	3.003	5.211	4.635	7.369
Diameter error (%)	28.9	20.50	15.30	-14.13	-15.02
Depth error (%)	19.16	-14.20	15.80	-15.73	13.37

6. Conclusions

BNs are very natural tools for reproducing the random dependence structure of defect geometry parameters estimation based on ECNDT. In particular, BNs used in this paper are very simple and powerful, and their parameters can be easily learnt from the topology of the networks and experimental data. The WPA de-noising method improves the performance of estimation based on BNs when using time-domain signals. The proposed method allows us to obtain the full distributions of needed prediction variables accounting for all the information available (evidences). Two experiments have been carried out. In the two examples, the BNs model deals with all variables and allows determining means and variances, given the inspection signals. In particular, the probability distributions supplied much more information than the other methods.

In this paper, the multidimensional Gaussian assumption of the defect parameters has been taken. Nevertheless, in real problems where the distributions are nonuniform, a non-Gaussian assumption also could be more suitable. In fact, the validity of the methods is not restricted to the particular case of multidimensional Gaussian distributions, but to more general distributions (Gamma, Poisson, normal, etc.). The BNs model can handle the problem that each conditional distributions of each variable given its parents can be any distributions. However, these possibilities are out of the scope of this paper, but it is actually the topic of current and future work of the authors. At the same time, considering the uncertainties in the data such as measurement errors, small sample size, stochastic nature of inspection, additional efforts should be done to add more nodes which can substantially approximate more precisely the real model of defect parameters estimation. It will be helpful to analyze the EC signals more accurately in detail and lead to more precise predictions.

Acknowledgments

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