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Identification of crack profiles using genetic programming and fuzzy inference

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Abstract

This paper deals with a quantitative nondestructive evaluation in eddy current testing for steam generator tubes of nuclear power plants by using genetic programming (GP) and fuzzy inference system. Defects can be detected as a probe impedance trajectory by scanning a pancake type probe coil. An inference system is proposed for identifying the defect shape inside and/or outside tubes. GP is applied to extract and select effective features from a probe impedance trajectory. Using the extracted features, a fuzzy inference system detects presence, position, and size of a defect of test sample. The effectiveness of the proposed method is demonstrated through computer simulation studies.

Keywords: Genetic programming; Fuzzy inference; Eddy current

1. Introduction

Recently, there has been growing interest of quantitative nondestructive evaluation of material structure used in nuclear power systems. The structural integrity of steam generator tubes of the power plant has a critical issue on safety and trustability of the system. To this end, many efforts on QNDE are focused into the software developments using advanced ECT (eddy current testing) technology [1]. The developments based on inverse analysis are one successful approach for QNDE techniques [2–4]. These methods involve an attempt to characterize structural flaws that might not be detectable by visual inspection. Although those techniques provide very accurate defect information, tremendous computational costs are required. In fact, computational methods are indispensable to detect material flaws arising in thousands of heat exchanger tubes of steam generators in short time. *Soft Computing* is a feasible technique for reducing the computational cost mentioned above. Soft computing proposed by Zadeh [5,6] is a new concept for information processing and its objective is to realize a new approach for analyzing and creating flexible information processing of human being such as sensing, understanding, learning, recognizing and thinking. Soft computing includes fuzzy computing, neural computing, and evolutionary computing. While neural computing simulates physiological features of human brain, fuzzy computing simulates include fuzzy computing, neural computing, and evolutionary computing. While neural computing simulates physiological features of human brain, fuzzy computing simulates psychological features of human brain. Fuzzy computing basically deals with human linguistic representations and therefore fuzzy inference system (FS) can be constructed by human knowledge within a specific domain. In this way, fuzzy inference has an advantage of the easy introduction of human knowledge. In fact, human knowledge is used in monitoring systems of the nuclear plants, but it is very difficult to extract important or meaningful information from the measured data in the monitoring systems. Therefore, we propose an FS with an automatic feature extraction mechanism. Genetic programming (GP) that automatically generates functions is applied to extract and select effective features from the measured data. The features are used as input data into the FS. In this paper, we apply the proposed method to identify the defect shape from the probe impedance trajectory.

2. GP-based FS

Input information of an inference system is often translated into qualitative information by human operators. In this

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paper, we propose an inference system with translation preprocessing. The preprocessing includes feature extraction and feature selection. To build a well-performed inference system, the preprocessing is very important because the translated information differentiates an output from the other outputs. By using soft computing methods, there might be three different procedures for the preprocessing [7]:

1. GP + NN (FS),
2. GA + NN (FS), and
3. GP (GA) + NN (FS) + GP, etc.

Basically neural network (NN) or FS is used as the inference system. For case 1, the GP plays the role of feature extraction, i.e., the GP translates a set of given raw data into meaningful data. For case 2, the genetic algorithm (GA) plays the role of feature selection, i.e., the GA fundamentally reduces input dimensions to the inference system (NN, or FS). In case 3, the last GP plays the role of post-processing. In this way, the coevolution (cooptimization) of GP (GA) and FS (NN) is used to generate well-performed inference systems. In this paper, we adopt the system of GP (GA) + FS as shown in Fig. 1. The GP (GA) extracts and selects effective features from the measured data and FS makes the shape data from the extracted information.

2.1. GP for feature extraction and selection

Evolutionary computation is a field of simulating evolution on a computer. From the historical point of view, the evolutionary optimization methods can be divided into three main categories, GA, evolutionary programming and evolution strategy [8–10]. These methods are fundamentally iterative generation and alternation processes operating on a set of candidate solutions, which is called a population. All the population evolves toward better candidate solutions by selection operation and genetic operators such as crossover and mutation. The selection decides candidate solutions into the next generation, which reduces the search space spanned by the candidate solutions. It is experimentally known that the GAs can obtain near or approximately optimal solutions with less computational cost. GP is an extension of GA using a structural coding method. GP proposed by Koza [9,10] can deal with the tree structure and have been applied for generating computer programs. Next, we describe how to apply GP for the feature extraction. A candidate solution of

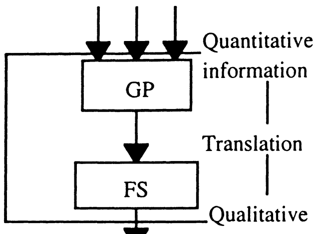

Fig. 1. GP-based FS.

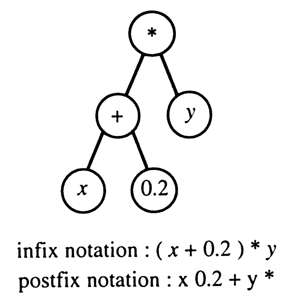

Fig. 2. A syntax tree based on postfix notation.

functions is composed of binary operator, unary operator, variables, and constants. Here a function is represented by the postfix notation. Fig. 2 shows an example of a function represented by the postfix notation. Using the postfix notation, we can deal with one-dimensional array of string. Fig. 3 illustrates a candidate solution representing multiple functions. The candidate solution includes validity parameters for the feature selection and functions for the feature extraction. The combination of functions is determined by the validity of each function. This representation of candidate solutions realizes the optimization of feature extraction and selection at the same time. A population is composed of candidate solutions and evolves through genetic operators and selection. In the next step, genetic operators generate new candidate solutions. Crossover exchanges the combination of functions and subtrees and between two candidate solutions. Fig. 3 shows an example of subtree-based crossover acting on functions. The crossover randomly finds subtrees and exchanges them between two candidate solutions. In this optimization problem, two types of mutations can be used for the search. The first one is to change the validity parameters for functions and symbols used in functions. A validity parameter is changed with the other symbol. The unary (binary) operator is replaced with the other unary (binary) operator. The other is to exchange the structure of function by replacement.

2.2. Fuzzy inference for identification of crack shapes

Fuzzy theory provides us the linguistic representation such as 'slow' and 'fast'. Fuzzy theory [5,6] expresses a degree of truth, which is represented as a grade of a membership function. The fuzzy logic is a powerful tool for non-statistic and ill-defined structure. FS is based on the concept of fuzzy set theory, fuzzy if–then rule, and fuzzy reasoning. The fuzzy reasoning derives conclusions from a set of fuzzy

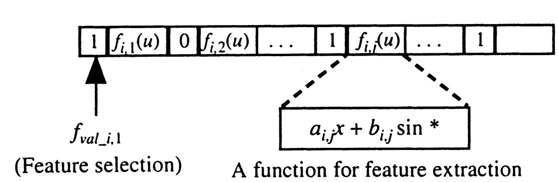

Fig. 3. A candidate solution including multiple functions.

if–then rules. FS implements mapping from the input space to the output space by a number of fuzzy if–then rules. In this paper, we use a simplified fuzzy inference method for identification of crack shapes. In general, a fuzzy if–then rule using the simplified fuzzy inference method is described as follows:

IF u_1 is $A_{i,1}$ and ... and u_j is $A_{i,j}$ and ... and u_n is $A_{i,n}$

THEN y_1 is w_i^1 ... and y_j is w_i^r and ... and y_s is w_i^s

where $A_{i,j}$ is a membership function for the jth input of the ith rule, w_i^r a singleton for the rth output of the ith rule, and n and s the numbers of inputs and outputs, respectively. A set of input data is described as $\{\mathbf{u}\}$ in the following:

$$\{\mathbf{u}\} = T \circ \{\Delta Z_d\}(\mathbf{q}) \tag{1}$$

where T is a function generated by GP. The activation degree of the ith rule ($i = 1, 2, \ldots, n$) is calculated by

$$\mu_i(\mathbf{u}) = \prod_{j=1}^{n} \mu_{i,j(i,k)}(u_i) \tag{2}$$

Next, we obtain the rth resulting output ($r = 1, 2, \ldots, s$) by weighted average as follows:

$$\hat{q}_r(\mathbf{u}) = \frac{\sum_{k=1}^{m^n} \mu_k(\mathbf{u}) w_k^r}{\sum_{k=1}^{m^n} \mu_k(\mathbf{u})} \tag{3}$$

This simplified FS can be regarded as an adaptive fuzzy NN [6]. When q_r is the target output, the error function is defined as

$$E(\mathbf{w}) = \frac{1}{2} \sum_{r=1}^{s} |q_r - \hat{q}_r(u; \mathbf{w}^r)|^2 \tag{4}$$

When the condition parts (membership functions) are fixed, we can easily train the output, w_i^r, of the kth rule according to the following delta rule based on the error function:

$$w_k^r(t+1) = w_k^r(t) - \tau \left. \frac{\partial E}{\partial w_k^r} \right|_{w_k^r = w_k^r(t)} \tag{5}$$

$$\frac{\partial E}{\partial w_k^r} = \frac{\partial E}{\partial q_r} \frac{\partial q_r}{\partial w_k^r} = -(q_r - \hat{q}_r(\mathbf{u}; \mathbf{w})) \frac{\mu_k(\mathbf{u})}{\sum_{k=1}^{m^n} \mu_k(\mathbf{u})} \tag{6}$$

$$w_k^r(t+1) = w_k^r(t) + \tau \frac{\mu_k(\mathbf{u})}{\sum_{k=1}^{m^n} \mu_k(\mathbf{u})} \delta^r(t) \tag{7}$$

Fig. 4 illustrates the total architecture of GP-based FS for the identification of crack shape. The objective is to find an FS that minimizes errors between the target outputs and the inference results, while simultaneously reducing input dimensions to FS. In addition, the functions generated by GP are indirectly evaluated through the error function of FS. Consequently, if the generated functions can extract features for the crack identification well, FS can be well trained by the delta rule. Therefore, the evaluation function of GP consists of the error function E, the number of the generated functions, and the length of candidate solution as follows:

$$f_{it} = W_1 E + W_2 n_i + W_3 L_i, \quad L_i = \sum_{j=1}^{m} f_{\mathrm{val}\_i,j}, \; f_{\mathrm{val}\_i,j} = \{0, 1\} \tag{8}$$

where $f_{\mathrm{val}\_i,j}$ is a validity of the jth function of the ith candidate solution, L_i the gene length of the candidate solution, and W_1, W_2, and W_3 the weight coefficients. The evolution of candidate solutions depends on the combination of genetic operators and selection mechanism. We apply a steady-state genetic algorithm (SSGA). In SSGA, only a few existing solutions are replaced by new candidate solutions generated by genetic operators in each generation [11]. Generally, the worst candidate solutions are eliminated. Since the objective of the above evaluation function is minimization, the candidate solution with the maximal value (i.e., the greatest error) is eliminated in the selection.

3. Computational experiments

The material properties of inspected specimen and experimental conditions are referred from [2]. The problem treated

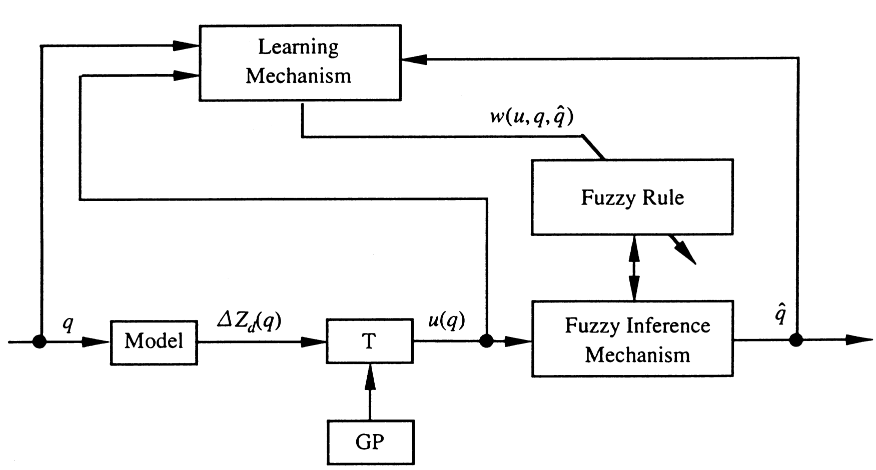

Fig. 4. A block diagram of fuzzy learning mechanism with functions (T) generated by GP.

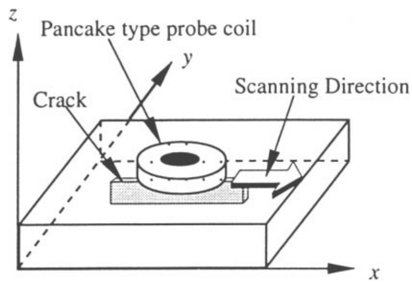

Fig. 5. Sample material and measurement method.

Table 1
Genotype and operators

Genotype	Operators
1	+ (binary operator)
2	− (binary operator)
3	∗ (binary operator)
4	max (binary operator)
5	min (binary operator)
6	sin (unary operator)
7	cos (unary operator)

here is to characterize crack depth inside and/or outside sample materials. Fig. 5 depicts the overall configuration of the ECT considered here. For the ECT model in Fig. 4, we use the hybrid FEM–BEM scheme based on A–ϕ method [4]. Table 1 shows the genotype used in GP. The number of candidate solutions is 150. The maximal length of a candidate solution is 600. The number of membership functions and shape information (outputs from FS) are 3 and 6, respectively. The number of teaching and testing data are taken as 30 and 4, respectively. Fig. 6 shows inference results for testing data where we used FS after 1000 generations (150 000 evaluations). In the figure, the black line indicates the inference results. The inference results show that the obtained FS can identify the crack shape of the testing data. Fig. 7 shows the learning curve of FS by the delta rule. Since the error is decreased by delta rule, the extracted features by GP are important for FS to learn the inference rules. Fig. 8 illustrates the scanning trajectory of the pancake-coil for the case of oblique scanning directions ($\theta = 1, \ldots, 4$). Fig. 9 shows the scanning process for the

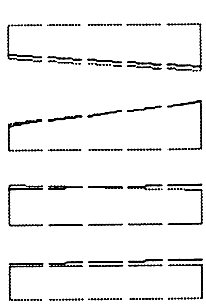

Fig. 6. Inference results for testing data of obtained GP-based FS.

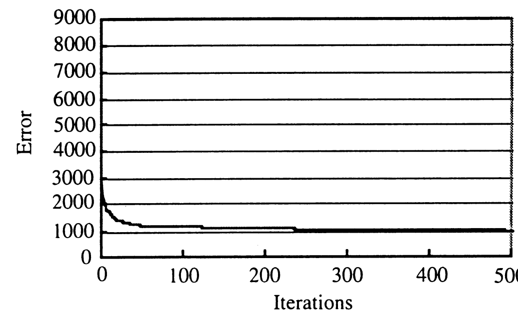

Fig. 7. Learning curve of FS by delta rule.

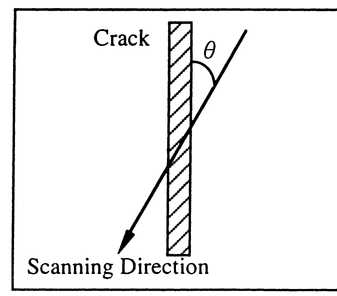

Fig. 8. Experimental example A.

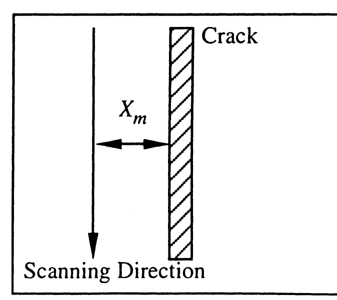

Fig. 9. Experimental example B.

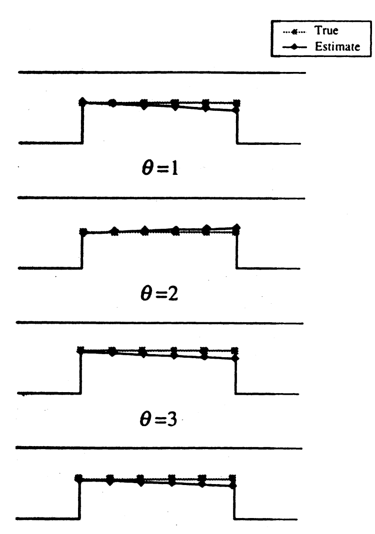

Fig. 10. Inference results for testing data of the obtained GP-based FS (example A).

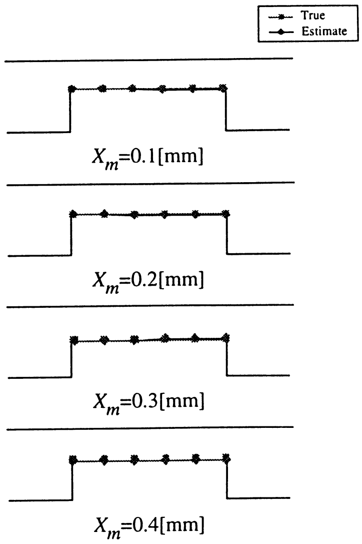

Fig. 11. Inference results for testing data of the obtained GP-based FS (example B).

case of the parallel scanning direction from the crack ($X_m = 0.1, \ldots, 0.4$ (mm)). Here the flat data of crack shape were used as testing data. Figs. 10 and 11 show simulation results of testing data.

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