[Regular Paper]

Defect Reconstruction of Submarine Oil Pipeline from MFL Signals Using Genetic Simulated Annealing Algorithm

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This paper presents a genetic simulated annealing algorithm (GSAA)-based inverse algorithm for reconstructing the shape of a two-dimensional defect from the magnetic flux leakage (MFL) signals. In the algorithm, the GSAA formulated by incorporating the simulated annealing technique into the mutation operator of the standard genetic algorithm (GA) is employed to solve the optimization problem in the inverse problem, and a radial-basis function neural network (RBFNN) is utilized as the forward model. Experimental results demonstrated that the GSAA-based inverse algorithm is more accurate and is more robust to noise than the GA-based inverse algorithm.

Keywords

Oil pipeline, Defect reconstruction, Genetic algorithm, Simulated annealing, Inverse problem

1. Introduction

The magnetic flux leakage (MFL) method is now established as the most widely used in-line inspection technique for the evaluation of submarine oil pipelines. Inverse problems in MFL nondestructive evaluation (NDE) involve determining the defect parameters such as the length, width, or defect shape based on the information contained in the measured signals. Inverse problems are commonly solved using iterative methods¹⁾. These methods involve solving well-behaved forward problem in a feedback loop. Conventionally, numerical models such as the finite-element model (FEM) are to represent the forward process. However, iterative methods using the numerical-based forward models are computationally expensive. Neural networks are utilized for solving inverse problems in NDE^{1)~4)} and used to represent the forward process in the iterative methods¹⁾. The advantages of using neural networks are that neural networks can approximate any arbitrary function and can be trained off-line. Hwang *et al.*³⁾ described the use of a wavelet basis function (WBF) neural network to predict three-dimensional defect profiles. Ramuhalli *et al.*⁴⁾ used two neural networks in feedback configurations. In this method, a forward network is used as the forward model, and an inverse network is used to predict the profile given the measured MFL signals. Ramuhalli *et al.*¹⁾ proposed a

neural-network-based iterative inversion algorithm using neural networks as a forward model. In the algorithm, the problem of defect profile reconstruction from MFL signals is formulated as an optimization problem, where the defect profile is updated using a combination of gradient descent and simulated annealing to minimize the error between the measured signal and the model predicted signal. Arkadan *et al.* introduced a genetic algorithm based approach for crack identification⁵⁾. Li *et al.* presented a genetic local search (GLS) algorithm for reconstructing the profiles of 3-D defects from eddy-current NDE signals⁶⁾.

This paper presents a genetic simulated annealing algorithm (GSAA)-based inverse algorithm for 2-D defect reconstruction from MFL signals. In the algorithm, a radial-basis function neural network (RBFNN) is utilized as forward model, and the GSAA which is formulated by incorporating the simulated annealing technique into the mutation operator of the genetic algorithm is used to solve the optimization problem in the inverse problem. Experimental results show that the GSAA-based inverse algorithm is more accurate and is more robust to noise than the GA-based inverse algorithm.

2. Development of Genetic Simulated Annealing Algorithm

The genetic algorithm (GA) is a search mechanism based on the principles of natural selection and population genetics and has been widely applied in a number

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of different areas^{7),8)}. Instead of a point-by-point search, the GA offers a parallel search of the solution space rather than a single region. Hence, the GA can find a near global optimal solution and consequently avoid the local minimum solution possibly encountered in the gradient-descent-based optimization approach. A canonical GA usually begins with a randomly generated set of potential solutions, called the initial population. Each member in the population represents a possible solution of the problem. A fitness function is used as a measure of the closeness of each member in the population to the global optimum solution. Then, members from the population are selected to produce new members, called descendents or children, by applying stochastic operators to the selected members. The selection mechanism often favors the highly fit members in such a way that the members more close to the global optimal solution are assigned higher probabilities for producing children. The most common genetic operators are crossover and mutation. A crossover operator combines the features presented in parents to produce descendents. Crossover methods include single-point crossover, two-point crossover and uniform crossover. A mutation operator slightly perturbs a selected member in a random manner. Typical mutation methods include Gaussian mutation⁹⁾ and uniform mutation. A new generation is then formed using the descendents to replace part or all of the members in the current population. Crossover operations ensure that the new population inherits highly fit features while mutation operations may add previously unexploited features into the population. It is hoped that in doing so, the population would, very likely, drift to a global or near global solution after a number of generations. This search process is called genetic evolution. Genetic algorithm based optimization approaches involve consideration of five key issues: parameter representation, measure of the fitness of potential solutions, an initial population, genetic operators to update the population, and termination criterion.

The simple canonical GA may be trapped by local optima or converge prematurely when solving the optimum of large-scale combinatorial optimization problems. The performance of canonical GA can be improved by introducing more diversity among the members in the early stage of the solution process so that the premature convergence can be prevented. In order to avoid premature convergence, the genetic local search (GLS) algorithm⁶⁾ casts the simulated annealing method into the frame of the canonical GA, and the genetic annealing algorithm (GAA)¹⁰⁾ incorporates the probabilistic acceptance test technique of simulated annealing into the incremental genetic algorithm (IGA). Premature convergence can also be prevented by using mutation operators with various mutation rates or mutation ranges^{9)~13)}. This study developed GSAA by in-

corporating the simulated annealing technique into the mutation operator of the canonical GA. In a similar way to the GAA¹⁰⁾, the simulated annealing technique is used to control the variance for Gaussian mutation in the GSAA. The member to be mutated is perturbed according to the Gaussian probabilistic distribution function (GPDF) with its variance controlled by the simulated annealing technique. The perturbation of the i th component of the selected member can be written as

$$x_i' = x_i \pm \Delta x_i \quad (1)$$

where Δx_i is the amount of perturbation on the x_i . Using the simulated annealing technique, the amount of perturbation can be expressed as

$$\Delta x_i = (x_{i\max} - x_{i\min}) \cdot T_k \cdot \text{randn}(0, 1) \quad (2)$$

where $\text{randn}(0, 1)$ is a Gaussian random number with zero mean and unit variance, $x_{i\max}$ and $x_{i\min}$ denote the extreme values of x_i in the search space, and T_k is the temperature of the k th generation and is reduced according to the following equation:

$$T_k = r^{(k-1)} T_0 \quad (3)$$

where T_0 is the initial temperature, and r is the temperature reduction factor. It should be noted that the Gaussian mutation with the simulated annealing technique reduces to the conventional Gaussian mutation when $r = 1$. Since the perturbation is centered on the original value of x_i , smaller perturbation implies a more local search, whereas larger perturbation is better for introducing diversity. Equation (2) shows that the amount of perturbation is regulated and reduced as the evolution process progresses.

The GSAA can be summarized as follows.

- (1) Randomly build an initial population.
- (2) Create a sequence of new populations, or generations. At each step, the algorithm uses the individuals in the current generation to create the next generation. To create the new generation, the algorithm performs the following steps:
 - a. Score each member of the current population by computing its fitness value.
 - b. Scale the raw fitness scores to convert them into a more usable range of values.
 - c. Select parents based on their fitness using a roulette wheel selection method.
 - d. Produce children from the parents. Children are produced by performing uniform crossover and by performing Gaussian mutation with simulated annealing technique which is used to control the variance of the Gaussian mutation.
 - e. Replace the current population with the children to form the next generation.
- (3) The algorithm stops when the stopping criterion is met. The average fitness value of the population is used as the stopping criterion. The algorithm stops when the average fitness value of the population is greater than a predefined threshold. Otherwise, return

Fig. 1 Block Diagram of the GSAA-based Inverse Algorithm

to Step 2.

3. GSAA-based Signal Inverse Algorithm

Figure 1 shows the block diagram of the GSAA-based inverse algorithm. In this approach, the radial-basis function neural network (RBFNN)¹⁴⁾ is used to model the forward process and the GSAA described above is used to solve the optimization problem in the iterative process. The procedure begins with a set of randomly created initial defect parameters. The RBFNN forward model is used to predict the signals corresponding to these defect parameters. These predicted signals are then compared to the measured signal and the corresponding value of the fitness function is computed. If the average fitness value f_{avg} is greater than a predefined threshold ε , the iterative process is terminated. Otherwise, genetic operators are employed to update the defect parameters in the current defect parameter set. This algorithm stops until the termination criterion is met, and the fittest defect shape in the last iterative process is then viewed as the optimal defect shape corresponding to the measured signal.

The radial-basis function neural network (RBFNN) is used to model the forward process to predict the MFL signal $\mathbf{y} = (y_1, y_2, \dots, y_M)$ associated with the defect shape $\mathbf{x} = (x_1, x_2, \dots, x_N)$, where N is the number of defect parameters and M is the dimension of the output. The defect parameter x_i and the corresponding signal y_i are presented to the input and output layer nodes. The I/O relation for the RBFNN using Gaussian-basis functions is given by¹⁾

$$y_l = \sum_{j=1}^H w_{lj} \exp\left(-\frac{\|\mathbf{x} - \mathbf{c}_j\|^2}{2\sigma_j^2}\right) \quad (4)$$

$$j = 1, 2, \dots, H, \quad l = 1, 2, \dots, M$$

where H is the total number of basis functions used, w_{lj} are the expansion coefficients or weights associated with each basis function, $\mathbf{c}_j$ is the center of the j th Gaussian-basis function, and σ_j is the width of the Gaussian function. The orthogonal least squares learning algorithm provides a simple and efficient means for fitting radial basis neural networks¹⁵⁾.

A cost function is defined as the sum-squared error between the desired measured signal $\mathbf{d} = (d_1, d_2, \dots, d_M)$ and the actual predicted output $\mathbf{y} = (y_1, y_2, \dots, y_M)$ of the neural network and is computed as

$$E = \sum_{i=1}^M (d_i - y_i)^2 \quad (5)$$

In a similar way to the method of Yue *et al.*⁶⁾, the minimization of the above cost function is recast as maximizing the following fitness function:

$$f = \frac{1}{1 + C \sum_{i=1}^M (d_i - y_i)^2} \quad (6)$$

where C is a constant. The maximum value of the fitness function is 1.0. The constant C controls the relative ratio between the global maximum and local maxima. It can be seen that $0 < f \leq 1$.

As a result, the defect reconstruction problem can be viewed as an optimization problem, which seeks defect parameters to maximize the fitness function. The optimization problem is solved using the ICGA described above.

For the specific 2-D defect reconstruction problem in this study, a candidate solution is represented by the defect shape $\mathbf{x} = (w, d)$, where w and d are the width and depth of the defect, respectively. As the values of defect parameters are continuous, real values are used to represent each defect parameter.

The inverse algorithm where the optimization problem is solved using the canonical GA is referred to as the GA-based inverse algorithm.

4. Experimental Results

Experiments are presented to verify the effectiveness of the GSAA-based inverse algorithm and to compare it with the GA-based inverse algorithm. The MFL data are generated by means of a 2-D finite element model (FEM), and only the cross section of the defect with varying widths and depths is modeled. A set of 240 defects was used to generate the corresponding MFL signals. The defects varied in width from 1 to 7 inch and depth from 0.15 to 0.85 inch in a sample of unit thickness. As described in the technical paper by

Table 1 Results Comparing the Performance of the GSAA-based and GA-based Inverse Algorithms for a Defect (2.6 inch width, 0.60 inch (60%) depth)

GA				GSAA			
Width [inch]	Depth [%]	G	E	Width [inch]	Depth [%]	G	E
2.4542	60.0772	12	4.10E-05	2.6116	59.9912	14	1.70E-06
2.5915	60.0588	7	1.53E-06	2.6553	59.8454	8	8.73E-06
2.6737	60.0127	8	1.18E-05	2.5883	60.0044	12	1.60E-06
2.6095	64.5363	9	1.56E-04	2.5648	60.1461	6	7.15E-06
2.6011	60.0316	8	1.39E-06	2.5244	60.1404	8	1.57E-05
2.5823	59.9807	10	1.90E-06	2.6554	60.0536	11	7.09E-06
2.5296	65.4508	14	1.37E-04	2.6015	60.0583	8	1.40E-06
2.6183	59.7621	11	2.11E-05	2.6021	60.0004	11	1.42E-06
2.7329	54.9535	4	1.70E-04	2.6100	60.0754	10	1.63E-06
2.5390	60.1466	12	1.23E-05	2.5415	60.0988	11	8.62E-06

Table 2 Results Comparing the Performance of the GSAA-based and GA-based Inverse Algorithms for Defects with Various Width and Depth Parameters

True parameters		GA				GSAA			
Width [inch]	Depth [%]	Width [inch]	Depth [%]	G	E	Width [inch]	Depth [%]	G	E
1.8	35	1.73	35.23	12	1.61E-05	1.79	35.00	7	1.43E-06
1.8	80	1.83	80.05	9	1.05E-05	1.79	80.00	6	3.91E-06
2.2	60	2.16	59.95	11	5.05E-06	2.23	60.05	10	6.38E-06
2.6	50	2.54	49.94	7	7.47E-06	2.63	50.09	7	3.49E-06
3.0	60	2.95	60.01	12	9.71E-06	3.02	59.95	8	5.00E-06
3.4	60	3.29	59.92	9	2.76E-05	3.41	59.95	13	1.57E-06
4.2	35	4.18	34.75	9	1.64E-05	4.16	34.89	11	3.22E-06
5.0	35	4.94	35.06	11	4.16E-06	4.96	35.03	10	3.28E-06
5.4	75	5.43	74.71	11	1.33E-04	5.40	75.05	10	3.21E-06

Ramuhalli *et al.*¹⁾, of these 240 defect shape-MFL signal pairs, 210 were used to train the neural networks while 30 were used as part of the test database with no overlap between the training and test sets. The radial-basis function neural network (RBFNN) is trained using the orthogonal least squares learning algorithm¹⁵⁾. In GA and GSAA, the real value is used to represent the member in the population, uniform crossover and Gaussian mutation are used, and an initial population of size 300 is built randomly. The parameters in Eq. (3) used in the GSAA are set as $T_0 = 1$ and $r = 0.9$.

Table 1 shows the results of 10 independent trials for 2.6 inch width, 0.60 inch (60%) deep defect comparing the performance of the GSAA-based and GA-based inverse algorithms. In the **Table 1**, G represents the number of generations required for the convergence of the algorithms, and E represents the value of the cost function defined by Eq. (5) after the convergence of the algorithms. It can be seen that the GSAA-based inverse algorithm reaches the global optimum for all 10 trials, whereas the GA-based inverse algorithm is trapped in local optima for some trials. In addition, the GSAA-based inverse algorithm is more accurate than the GA-based inverse algorithm.

Table 2 shows the results comparing the perfor-

mance of the GSAA-based and GA-based inverse algorithms for defects with various width and depth parameters. It can be seen that the GSAA-based inverse algorithm reaches all various defects, whereas the GA-based inverse algorithm is trapped in local optima for some defects. In addition, the GSAA-based inverse algorithm is more accurate than the GA-based inverse algorithm.

In fact, the signals to be inverted are usually corrupted with additive white Gaussian noise. The noise level is described by the signal-to-noise ratio (SNR), which is defined as $SNR = 10 \log(P_s/\sigma^2)$ where P_s and σ^2 are signal power and noise power, respectively. **Table 3** shows the results of GSAA-based and GA-based inverse algorithms for a 3.0 inch width, 0.60 inch (60%) deep defect using noisy signals with different SNR. These results indicate that the GSAA-based inverse algorithm is more robust to noise than the GA-based inverse algorithm.

The above results show that the GSAA-based inverse algorithm can accurately reconstruct the defect parameters and exhibits better performance than the GA-based inverse algorithm.

Table 3 Results Comparing the Performance of the GSAA-based and GA-based Inverse Algorithms for a Defect (3.0 inch width, 0.60 inch deep) with Noise

SNR [dB]	GA				GSAA			
	Width [inch]	Depth [%]	G	E	Width [inch]	Depth [%]	G	E
45	3.0566	59.9853	8	9.58E-06	3.0201	60.0441	10	4.84E-06
40	3.0165	60.2636	9	4.63E-05	3.0211	59.9578	6	4.88E-06
35	2.8499	60.1154	8	5.79E-05	2.9851	60.0462	10	5.30E-06
30	3.1143	59.7069	8	7.30E-05	2.9716	59.8472	8	1.48E-05
25	2.9919	59.7125	7	6.54E-05	3.0101	59.9958	17	4.21E-06
20	3.0808	59.7612	4	3.79E-05	2.9978	60.0339	7	4.41E-06
15	2.8850	64.6577	9	1.49E-04	2.9637	60.0486	16	8.03E-06
10	3.0471	60.2002	6	2.12E-05	2.9968	59.8536	7	1.07E-05

5. Conclusions

A GSAA-based inverse algorithm is proposed for 2-D defect reconstruction of submarine oil pipelines from MFL signals, where the GSAA is formulated by incorporating the simulated annealing technique into the mutation operator of the canonical genetic algorithm. In the proposed inverse algorithm, a radial-basis function neural network (RBFNN) is utilized as the forward model, and the GSAA is used to solve the optimization problem in the inverse problem. The GSAA can prevent the premature convergence of the canonical GA and improve the performance of the canonical GA by incorporating the simulated annealing technique into the mutation operator of the canonical GA. Experimental results have demonstrated that the GSAA-based inverse algorithm can accurately reconstruct the defect parameters, exhibits better performance and is more robust to noise in the MFL signals than the GA-based inverse algorithm.

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要 旨

遺伝的焼きなましアルゴリズム手法による送油パイプライン磁束漏洩信号からの瑕疵部形状の再現

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遺伝的アルゴリズムに焼きなまし法を組み入れ、初期において高く出現する突然変異率を徐々に低くしていく手法である遺伝的焼きなましアルゴリズム (GSAA) 法は最適化手法の一つとしてよく知られており、さまざまな分野において応用されている。また、同手法は単なる遺伝的アルゴリズム手法よりもその精度は優れており、雑信号の多いデータから有用な信号のみ

を抽出する場合に強みを発揮するといわれている。本論文においては海底送油用パイプラインの瑕疵の検査法として広く利用されている手法である磁束漏洩非破壊検査法の信号処理へのGSAA法の適用性を実験結果に基づき検討した上で、精度よく種々の瑕疵パラメーターを再現することが可能であるとの結論を導き出している。

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