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2-D defect profile reconstruction from ultrasonic guided wave signals based on QGA-kernelized ELM

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ABSTRACT

The reconstruction of defect profiles based on ultrasonic guided waves means the acquisition of defect profiles and parameters from ultrasonic guided wave inspection signals, and it is the key for the inversion of ultrasonic guided waves. A method for the reconstruction of 2-D profiles based on kernelized extreme learning machine (ELM) is presented, and quantum genetic algorithm (QGA) is adopted to optimize the cost parameter C and kernel parameter γ of kernelized ELM. The input data sets of kernelized ELM are defect echo signals, and the output data sets are 2-D profile parameters. The mapping from defect echo signals to 2-D profiles is established. The sample database is achieved by practical experiments and numerical simulations. Then, 2-D profile reconstruction of artificial defects in ultrasonic guided wave testing is implemented with QGA-kernelized ELM. To compare the generalization performance and reconstruction results, another reconstruction model based on LS-SVM is designed simultaneously with the same kernel. Finally, experimental results indicate that proposed method possesses faster speed, lower computational complexity and better generalization performance, and it is a feasible and effective approach to reconstruct 2-D defect profiles.

1. Introduction

Pipelines are the most important facilities of the gas, oil and chemical industries. With the extension of the service time of the industrial pipelines, the damage caused by corrosion, external force or pipe material defects makes the pipeline security situation gradually deteriorated. Hence, nondestructive testing and evaluation has become an important approach to reduce losses and save inspection time. A number of different inspection technologies are available to inspect defected pipelines, ranging from magnetic flux leakage (MFL) to conventional ultrasonic waves [1–3]. For large and long facilities, conventional ultrasonic tests and evaluations are time-consuming works because each part of facilities needs to be scanned by placing huge number of transducers. Ultrasonic guided wave testing, propagating along a pipeline, has become a powerful technology for solving this issue. Ultrasonic guided waves can produce stresses throughout the entire thickness of the pipe, which means it is possible to detect surface and internal defects.

The reconstruction of defect profiles based on ultrasonic guided waves means acquiring defect parameters and rebuilding the defect profiles from reflected signals, and it is the key for the inversion problem of ultrasonic guided wave testing. Issues on how to locate the position of the defect on the axial and circumferential direction are discussed in [4]. Simulation results in [5] show that the arrival time and magnitude of damage-reflected wave packet change regularly with the increasing of damage depth or thickness. Split spectrum processing algorithm is used in ultrasonic guided wave-based damage identification [6]. The former researches on defect reconstruction are mainly based on the guided wave prediction theory, and they can detect the defects situating on the axial direction and the circumferential direction. However, they are incapable of achieving axial width and radial depth of defects. Artificial neural network is well-known for its remarkable learning ability, excellent linear and non-linear mapping ability, the better generalization performance and lots of successful applications. Therefore, this paper intends to accomplish 2-D defect profile reconstruction by using neural networks.

Support vector machine (SVM) has demonstrated good performance on classification problems and regression problems [7–9]. Least square support vector machine (LS-SVM) [9,10] uses equality optimization constraints instead of inequality optimization constraints in original SVM, which can be solved by least square methods instead of quadratic programming.

Extreme learning machine [11,12] was originally proposed as the training algorithm single-hidden layer feedforward networks (SLFNs), and then extended to the "generalized" SLFNs where the

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hidden nodes non-neuron alike [13,14]. In ELM, the hidden neuron parameters are randomly chosen without tuning, and the output weights are determined by calculating Moore–Penrose (MP) generalized inverse. Actually, in the view of optimization, ELM is consistent with SVM and has milder optimization constrains [15]. Compared to SVM, ELM requires fewer optimization constraints and results in simpler implementation, faster learning speed, and better generalization performance [15]. Recently, in [16], Huang et al. proposed a kernelized ELM and found that kernelized ELM actually simplifies the implementation of LS-SVM. Frénay et al. [17] applied the kernelized ELM to non-linear support vector regression (SVR). Zhong et al. [18] compared the kernelized ELM with LS-SVM on face recognition applications, and found that kernelized ELM achieves better recognition accuracy with much easier implementation and faster training speed.

Considering so many advantages of kernelized ELM, this paper presents a new method to reconstruct 2-D defect profile from ultrasonic guided wave signals based on kernelized ELM. Practical experiments and numerical simulations on propagation of $L(0,2)$ guided wave are conducted to build the sample database for profile reconstruction. And then, the mapping from the defect echo signals to 2-D defect profiles is established. In the implementation of the proposed method, quantum genetic algorithm (QGA) is adopted to optimize the cost parameter C and kernel parameter γ of kernelized ELM. To compare the generalization performance and reconstruction results, a LS-SVM network is trained with the same kernel at the same time. In the last section, the experimental results indicate that proposed method possesses fast speed, better generalization performance and lower computational complexity, and the proposed method is a feasible and effective approach for defect profile reconstruction.

2. Least square support vector machine (LS-SVM) for function estimation

Support vector machine (SVM) [7] is a machine learning system based on statistical learning theory. With the introduction of the epsilon-insensitive loss function, SVM has been extended to solve regression problems [8]. Least square support vector machine (LS-SVM) [9] proposed by Suykens and Vandewalle is an extension of the conventional SVM. LS-SVM provides equality optimization constraints instead of inequalities in the conventional SVM and achieves a least square solution by avoiding quadratic programming. Hence, the algorithm has excellent generalization performance and low computational cost in many applications [10].

A training dataset of N points $D=\{(\mathrm{x}_i, y_i)|i=1,2,3\cdots N.\}$ with input data $\mathrm{x}_i \in R^n$ and output data $\mathrm{y}_i \in R^n$ is given. In primal weight space, the following optimization problem is formulated as:

$$\min_{\omega,b,\xi} J(\omega,\xi)=\frac{1}{2}\|\omega\|^2+\frac{1}{2}C\sum_{i=1}^{N}\xi_i^2. \tag{1}$$

Subject to the constraints:

$$y_i=\omega^T\varphi(x_i)+b+\xi_i, \quad k=1,2,3,\cdots,N, \tag{2}$$

where $\varphi(\cdot): R^n \to R^{n_h}$ is the feature function mapping the input space to a usually high dimensional feature space, weight vector $\omega \in R^{n_h}$ in primal weight space, error variable $\xi_k \in R$, bias term b and C the cost parameter. The solution is obtained after constructing the Lagrange

$$L(\omega,b,\xi,\alpha)=\frac{1}{2}\|\omega\|^2 + \frac{1}{2}C\sum_{k=1}^{N}\xi_i^2-\sum_{k=1}^{N}\alpha_k\{\omega^T\varphi(x_k)+b+\xi_k-y_k\}, \tag{3}$$

where $\alpha_k \in R$ is Lagrange multiplier. Based on the Karush–Kuhn–Tucker theorem [19], the solution is given by the following set of linear equations:

$$\begin{bmatrix} 0 & 1_v^T \\ 1_v & \varphi(x_k)^T\varphi(x_l)+C^{-1}I \end{bmatrix}\begin{bmatrix} b \\ \alpha \end{bmatrix}=\begin{bmatrix} 0 \\ y \end{bmatrix}, \tag{4}$$

where $y=[y_1,y_2,y_3,\cdots,y_N]$, $1_\nu=[1,1,1,\cdots,1]$, and $\alpha=[\alpha_1,\alpha_2,\alpha_3,\cdots,\alpha_N]$. And according to Mercer's condition [20], there exists a mapping $\varphi(\cdot)$ and a kernel $K(\cdot,\cdot)$ such that

$$K=\varphi(x_i)^T\cdot\varphi(x_j)=K(x_i,x_j), \quad i,j=1,2,\cdots,N. \tag{5}$$

This finally results into the following LS-SVM model for function estimation

$$y(\boldsymbol{x})=\sum_{i=1}^{N}\alpha_i K(x,x_i)+b, \tag{6}$$

where α and b are the solutions to Eq. (4). $K(\cdot,\cdot)$ represents the high dimensional feature spaces that are nonlinearly mapped from the input space x. The LS-SVM approximates the function using Eq (5), and the popular Gaussian function is used as the kernel function

$$K(x,x_i)=\exp(-\gamma|x-x_i|^2), \tag{7}$$

where γ is a positive real value.

Note that in the case of Gaussian kernels, the cost parameter C in Eq. (1) and the kernel parameter γ in Eq. (7) should be chosen carefully.

3. Kernelized extreme learning machine (kernelized ELM)

Extreme learning machine (ELM) is a novel learning scheme for single hidden layer feedforward neural networks (SLFNs) [11,12,21–23]. In ELM, the output weights between the hidden layer and the output layer are directly calculated by using Moore–Penrose generalized inverse, while the input weights (connecting the input layer to the hidden layer) and hidden biases can be randomly chosen. In [13,14], ELM was extended to the generalized SLFNs where the hidden layer may not be neuron alike. Eq. (8) is the output of ELM for generalized SLFNs.

$$f_L(x)=\sum_{i=1}^{L}\beta_i h_i(x)=h(x)\beta \tag{8}$$

where $\beta=[\beta_1,\beta_2,\cdots\beta_L]^T$ is the vector of the output weights, and $h(x)=[h_1(x),h_2(x),\cdots h_L(x)]^T$ is the feature mapping vector that maps the input space to the hidden layer feature space H.

With the minimal norm least square method, the best output weights matrix is achieved [11,12]:

$$\beta=H^\dagger T, \tag{9}$$

where $H^\dagger$ [24,25] is the Moore–Penrose generalized inverse of matrix H, and H is the hidden layer output matrix. As can be seen in [26], the ridge regression theory shows that a positive value can be added to the diagonal of H^TH or HH^T, and the resultant solution is more stable and tends to have better generalization performance. Eq. (8) can be rewritten as

$$f(x)=h(x)H^T\left(\frac{I}{C}+HH^T\right)^{-1}T. \tag{10}$$

According to [16,18], if a feature mapping $h(x)$ is unknown to users, a kernel matrix for ELM can be defined as follows:

$$\Omega_{ELM}=HH^T : \Omega_{ELMi,j}=h(\mathrm{x}_i)\cdot h(\mathrm{x}_j)=K(x_i\cdot x_j). \tag{11}$$