Application Research for Ultrasonic Flaw Identification Based on Support Vector Machine

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Abstract. Automatic identification of flaws is very important for ultrasonic nondestructive testing and evaluation of pipelines. A novel automatic identification approach of flaws using support vector machine (SVM) is presented. Wavelet transform is applied to feature extraction of ultrasonic echo signals, and SVM is to perform the identification task. To validate this approach, some experiments are performed. The results show that unlike conventional and artificial neural networks (ANN) identification methods the new technique performs better than conventional evaluation ones with advantages of high identification performance for pipeline flaws, lower cost, excellent generalization.

Introduction

Pipelines prove to be the safest and the most economical means transporting large quantities of oil and gas resources. Maintenance of oil and gas pipelines is an issue of great concern for all oil and gas companies. But various flaws will inevitably occur and grow during the operations, such as crack, leakage, corrosion of the pipe wall, etc. Flaw detection and identification is a very important step to ensure pipelines safe operation. The traditional flaw detection suffers from complicated process, low accurate rate and off-line implement. The improved methods of flaw identification by artificial neural networks (ANN) can lead to the problems of overfit and bad generalization because of finite samples[1]. In this paper after de-noising the ultrasonic echo signals using wavelet transform and with a view of data mining, a novel approach using SVM classification is discussed to identify the flaws. The experiment results show that unlike conventional and ANN identification methods the new technique performs better than conventional evaluation ones with advantages of high efficiency, lower cost, easy implement on-line, excellent generalization. The approach provides a novel technique means for nondestructive flaw identification of various flaws.

Pipeline flaw identification based on SVM

A. Theory and principle of SVM

SVM initially came into prominence in the area of hand-written character recognition and is now being rapidly applied to many other fields, such as text categorization, computer vision, speech recognition and gene classification, etc.[2-3].

SVM is the approximate realization of the structural risk minimization method, analysis of the expression state of the linear separable pattern, which main idea is to establish a hyperplane as the decision hyperplane, the decision hyperplane can not only classify all the training samples correctly, but also among training samples make the distance between the points closest to the classification face and the classification face is the maximum. The detailed data can see references [4-5].

Flaw classification task involves training set and test set composed by data examples. Each example in training set includes a target value (class marker) and several attributes (characteristics). The objective of SVM is to produce a target value of data example containing only the attribute among a predicted test set.

Supposing that the training sample set is $\{(x_i, y_i)\}_{i=1}^{n}$ (in which input $x_i \in R^d$ and output $y_i \in \{-1,1\}$), the optimization problem of its hyperplane equation $w^T x + b = 0$ can be described as (in which w is the adjustable weight value vector and b is the offset) seeking the minimum of

$$\Phi(w) = \frac{1}{2} w^T w \tag{1}$$

when subjected to the constraint conditions of

$$y_i(w^T x_i + b) \geq 1 \qquad i = 1, 2, \cdots, n \tag{2}$$

The constrained optimization problem is called original problem, which can be solved by translating it into dual problem utilizing Lagrange multiplier method, namely seeking the maximum of

$$Q(\alpha) = \sum_{i=1}^{n} \alpha_i - \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} \alpha_i \alpha_j y_i y_j x_i^T x_j \tag{3}$$

when subjected to the constraint conditions of

$$\sum_{i=1}^{n} \alpha_i y_i = 0 \tag{4}$$

and

$$\alpha_i \geq 0 \qquad i = 1, 2, \cdots, n \tag{5}$$

After solving the optimal solution of the above coefficients, i.e. $\hat{\alpha}$, $\hat{w}$, $\hat{b}$, the optimal classification function can be obtained as

$$f(x) = \mathrm{sgn}(\hat{w}^T x + \hat{b}) = \mathrm{sgn}\left(\sum_{i=1}^{n} \hat{\alpha}_i y_i x_i^T x + \hat{b} \right) \tag{6}$$

For the nonlinear nonseparable pattern, the sample space can be mapped to the high dimensional feature space by the kernel function $K(x_i, x_j)$ and makes it become the linear separable pattern. An optimal classification hyperplane is constructed in the high dimensional feature space, thus realizing the classification. Compared with the linear separable pattern, the constraint condition (5) is changed into

$$0 \leq \alpha_i \leq C \qquad i = 1, 2, \cdots, n \tag{7}$$

where C can be used to control the punishment degree of the misclassified training samples.

Now the optimal classification function is changed into

$$f(x) = \mathrm{sgn}(\hat{w}^T \phi(x) + \hat{b}) = \mathrm{sgn}\left(\sum_{i=1}^{n} \hat{\alpha}_i y_i K(x_i, x) + \hat{b} \right) \tag{8}$$

The common kernel functions are linear kernel function, polynomial kernel function, RBF kernel function, and Sigmoid kernel function.

B. Selection of flaw classifier

SVM was initially proposed to solve the binary classification problems. There are two methods to solve the multi-classification problems of flaw at present[6]. One is to extend the basic binary class SVMs into multi-class SVMs by rewriting the optimization object function of the binary classifier, thus making SVM become the multi-classifier to solve the multi-classification problems, but which needs more operation. The other is to transform the multi-classification problems into binary classification problems gradually, namely the multiple-classifier can be composed of multiple binary class SVMs. For the latter there are two methods of one-against-rest and one-against-one. The method of one-against-rest is to distinguish the pattern of one class from the pattern of all rest classes using a classifier. So *n* flaw classifiers should be constructed for *n* types of problems, which advantage is *n* binary classification SVMs only need to be trained and its

classification speed is faster, which disadvantage is it has high requirement to every classifier. The method of one-against-one is to distinguish between every two of n types of training samples. So $n(n-1)/2$ classifiers are constructed respectively, which disadvantage is the excessive classifiers need be constructed in the case of existing more flaw types, each SVM should be compared in testing, in decision its speed is slower. In the real application, the selection of flaw classier should be considered comprehensively according to the concrete conditions.

C. Learning of SVM flaw identifier

Because the kernel function plays an important role in SVM, how to construct and select it and how to set up its parameters becomes the focus of attention. Now, there is still no unified theory for the selection of kernel function, statistical learning theory only gives some suggestions in this question. In this paper using Gaussian function as the kernel function, which advantage is that the location of function center, the number of function center, and the weight of network all can be determined automatically during the course of training, while the traditional RBF neural network depends on the experience knowledge to determine above parameters[7].

After selecting the kernel function, the threshold value of classification is obtained according to formula (2), then the values of (α_i, w, b) and the initial SVMs can be determined using formula (3), and the kernel function can be calibrated based on the results of classification testing. Finally the values of (x_i, y_i) is trained in terms of the above-mentioned algorithm to establish the optimal learning model $(\hat{\alpha}, \hat{w}, \hat{b})$ and find out the support vectors, so the SVM flaw classifier can be established according to formula (8).

D. Training and testing of SVM flaw identifier

Supposing that there are n types of pipeline flaws, the classifier is established using the method of one-against-rest, the steps of training and testing are as follows.

1) The obtained flaw eigenvector x is as the input of training samples, in which the output y of some kind of sample is set at 1, the output of the rest (n−1) types of samples is set at −1.
2) A kernel function is selected and the corresponding parameter and the error warning factor C are set up.
3) The samples are trained and tested to obtain the optimal classification function in this case.
4) In the same way the flaw classifiers corresponding to the n types of flaws can be established respectively.

In classification testing, the flaw eigenvector x of testing samples is as the input of the flaw classifier. If the output y of the m-th classification model is 1, it belongs to the m-th flaw, if the output of the m-th classification model is −1, it belongs to other flaws.

Application example

A. Establishment of sample data and feature extraction

In order to obtain different pipeline flaw signal, five types of welding flaw specimens were fabricated in laboratory, namely stomata, inclusion, incomplete fusion, incomplete penetration, crack. The experimental system was composed of probe, ultrasonic detector, A/D data acquisition card, computer, flaw analysis software, as shown in Fig.1.

In testing first the position of each flaw was located, and then the direction of probe was moved properly in order to obtain the maximum echo amplitude. The same testing process was carried out 40 times continuously, the ultrasonic testing waveforms were recorded and sent to the computer through A/D data acquisition card, two-hundred testing waveforms can be obtained. A wide-band focusing probe with 5MHz center frequency and 3mm diameter was used, in which the self-transmitting and self-receiving mode was adopted. The sampling frequency was 40MHz, and the length of the A-scan signal was 10000 points.

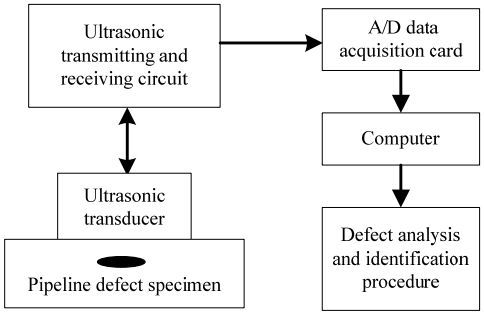

Fig.1. The ultrasonic testing experimental system diagram for pipeline flaw identification

Two-hundred flaw waveforms obtained from the experiment were denoised by wavelet transform, and its mean square values extracted from flaw signals were normalized and used as the eigenvalue. 150 eigenvalues from the flaw signals were selected as the training samples of the SVM flaw, and the rest 50 eigenvalues from the flaw signals were as the testing samples of the SVM flaw.

B. Analysis of testing results for SVM flaw identifier

According to above-mentioned method, selecting Gaussian kernel function and establishing SVM flaw identifier, a new set samples data x_i was input into the trained SVM identifier, the flaw classification can be obtained based on the output y_i and the testing results can be recorded, as shown in Table 1.

Table 1 Testing results of SVM flaw identification

Training sample number	SVM number	Testing sample number
150	24	50
Correct identification number	Error identification number	Identification accuracy (%)
47	3	94

Conclusion

SVM make full use the existing data information resources, the optimal solution can be obtained aiming at small sample and finite sample. Compared with the traditional flaw testing methods using instrument to identify the flaws, the methods of SVM flaw identification overcome the disadvantages of complicated process, low accuracy rate, influence upon anthropogenic factor. The classification results for pipeline welding flaws show that the pipeline flaw identification based on SVM has the advantages of low cost, high accuracy rate, high efficiency, excellent generalization, easy implement on-line, which solve the problem of often getting in the local minimum and difficult converging using neural network. SVM provides a new method to classify the pipeline flaws. The theory of SVM is still in the perfect stage, for instance in different condition the problem of selecting the kernel function should be further studied.

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