STUDY ON INTELLIGENT QUANTITATIVE RECOGNITION OF DEFECT IN PIPELINE MAGNETIC FLUX LEAKAGE INSPECTION

Yang Li-jian, Ma Feng-ming and Gao Song-wei

School of Information Science and Engineering, Shenyang University of Technology

Abstract

After to be preprocessed, such as elimination of signal variance and noise, image enhancement and so on, pipeline MFL (Magnetic Flux Leakage) image will be segmented with max entropy algorithm, and discontinuous defect image will be connected with dilation algorithm. The parameter position, width, etc. of defect can be calculated according to defect image. Precise length and depth of defect is recognized by trained BP neural network, and the error of recognition result is below 10%. The precision and reliability of neural network recognition is improved after axial and radial MFL signal is fused.

1. Introduction

The pipeline transportation is one of the fundamental modes in petroleum and natural gas long distance transportation. The pipeline security receives many countries' attention for a long time. Ferromagnetism pipeline forms various defect because of corrosion, attrition and mechanical damage. It is necessary for pipeline's security evaluation and maintenance to detect the pipeline regularly using pipeline detector and obtain the precise information of the defect, such as the position, the type, the depth and so on. Among various pipeline inspection technology MFL inspection is the most widespread and perfect one. It has good effect in ordinary defect detection, such as loss of metal.

Applying MFL inspection technology, the defect recognition is mainly completed by man at present. And in this way, the defect only can be recognized qualitatively but not quantitatively. With the improvement of MFL device's precision and the extension of inspection distance, the quantity of the data grows sharply. At present, there will be several dozens GB data to process when 100Km pipeline is detected. It need long time for man to analyze so massive data. So finding the intellective technology to recognize pipeline defect quantitatively is urgent.

In this paper, the pipeline MFL image is segmented with max entropy algorithm after to be preprocessed. And the defect is obtained according to its feature. The parameter width, area etc. of defect can be calculated based on defect image. Length and depth of defect is recognized by trained BP neural network. The precision and reliability of neural network recognition is improved after axial and radial MFL signal is fused.

2. Preprocessing the image

2.1 The feature of MFL signal

The MFL signal of a artificial defect (length:3mm, depth:35%)is shown in Fig.1.The real line is radial MFL signal and the broken line is axial MFL signal. The obvious variety and distinct peak value of the radial MFL signal nearby the defect makes defect recognized easily, so the radial signal is used primarily and the axial signal is secondarily.

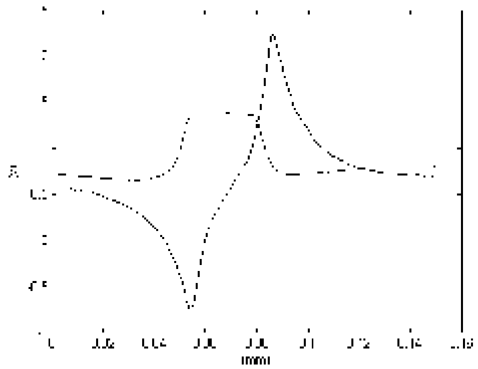

Fig 1*: the MFL signal of artificial defect*

2.2 Eliminating the influence of sensor's lift-off

In pipeline MFL inspection, the diversity of sensor's lift-off makes baselines of the sensor different. Because of the different baselines, there are strips in the image of MFL signal and the defect can be recognized difficultly. So it is necessary for the effective inspection data to be preprocessed and to eliminate the influence of sensor's lift-off. s_i represents the i_{th} sensor's signal in sensor array. m_i represents the average of inspection value.

$$\hat{s}_i = s_i - m_i \tag{1}$$

So $\hat{s}_i$ only represents the variety of MFL. The influence of lift-off is eliminated.

2.3 Radial MFL signal processing

The MFL image based on radial signal is shown in Fig.2.There is a bright area and a dark area which is relative to the positive and negative peak in Fig.2. This image is not appropriate for image segmentation based on threshold. So the Fig.3 will be obtained when the absolute value of the signal preprocessed as above add a base value. There are two bright areas in Fig.3.

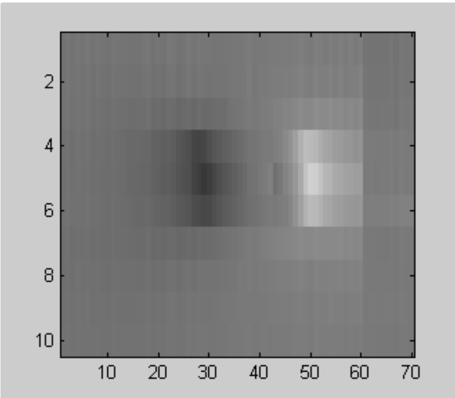

Fig 2*: radial MFL image of defect*

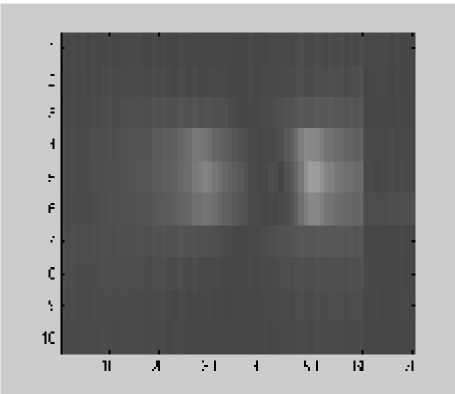

Fig 3*: radial MFL image after processing*

2.4 Median filter

During the inspection process, the device is always moving. The dithering of sensor conduces noise. And noise also appearances because the configuration of material to be detected is different from one other. The noise is stochastic and sporadic. It must be eliminated. Median filter is a better method to eliminate stochastic noise and sporadic noise. At the same time, it can save the edge of image commendably.

2.5 Image emphasizing

For the sake of being observed easily, the MFL image has to be emphasized because the brightness is not good or non-linearity cause contrast imperfect. In the experiment, the image is emphasized by transform gray scale or increasing base value.

3. Image segmentation

3.1 The max entropy algorithm

The gray scale of digital image is supposed as(G=l, 2 ... , L),all the amount of the pixels lies in gray scale i are denoted as f_i, all the amount of the pixels as N, therefore $N = \sum_{i=1}^{L} f_i$ .Suppose that P_i denotes the probability of grayness degree i in the image, so that $P_i = \frac{f_i}{N}$.

Denote the before entropy and the back entropy separately as below:

$$H_B(t) = -\sum_{i=1}^{t} \frac{P_i}{P_T} \log_2 \frac{P_i}{P_T} \tag{2}$$

$$H_w(t) = -\sum_{i=t+1}^{L} \frac{P_i}{1 - P_T} \log_2 \frac{P_i}{1 - P_T} \tag{3}$$

so the entropy

$$H_T(t) = H_B(t) + H_w(t) = \log_2 P_T(1 - P_T) + \frac{H_t}{P_T} + \frac{H_L - H_t}{1 - P_T} \tag{4}$$

thereinto ,

$$P_T = \sum_{i=1}^{t} P_i \, , H_t = -\sum_{i=1}^{t} P_i \log_2 P_i \, ,$$

$$H_T = -\sum_{i=1}^{L} P_i \log_2 P_i$$

When $H_T(t)$ gets the maximum, it corresponding threshold t* is the best threshold. viz.

$$H_T(t^*) = \max_{1<t<L} \{ H_T(t) \} \tag{5}$$

3.2 The MFL image segmentation

Segment the Fig.3 with the max entropy, the Fig.4 can be obtained. Segmenting Fig.4, two areas are obtained which are correspond to the two peak value areas of the radial signal. Therefore the Fig.4 revels the rough boundary of the defect, the parts between the two areas are still defect. In order to connect the discontinuous defect, to calculate the dilation element with dilation algorithm, a 1×17 matrix is adopted, then Fig.5 is obtained. Do this, a

basically accepted defect image can finally be gained. No more than this image is larger than the real defect.
For the MFL image gained from the real detection, we can also adopt the method of above to segment the image. The curve in Fig.6 is the real MFL one of the pipeline. In this figure, a obvious defect can be noted besides a ring welding. Dispose this chart like the method above, the results of the segmented defect and the welding shown in Fig.7 are satisfied.

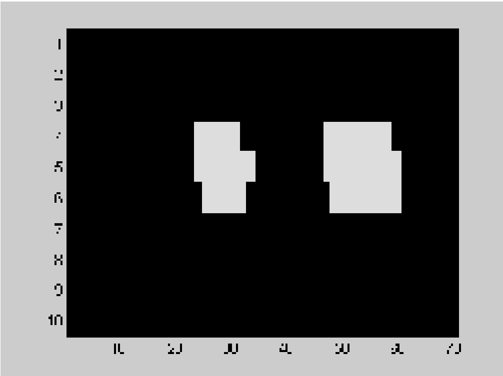

Fig 4*: Image of MFL after segmentation*

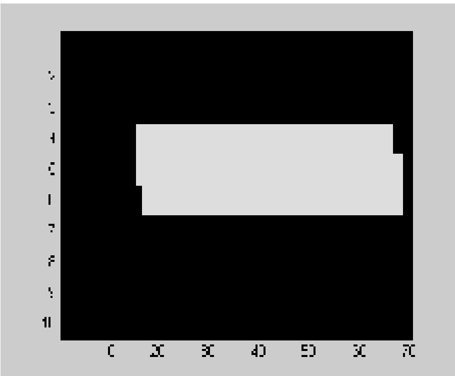

Fig 5*: Defect image of MFL after dilation*

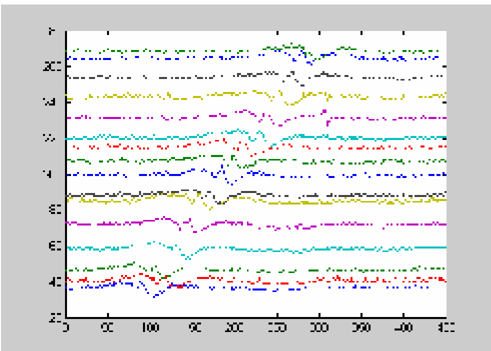

Fig 6*: Actual inspection MFL curve of pipeline*

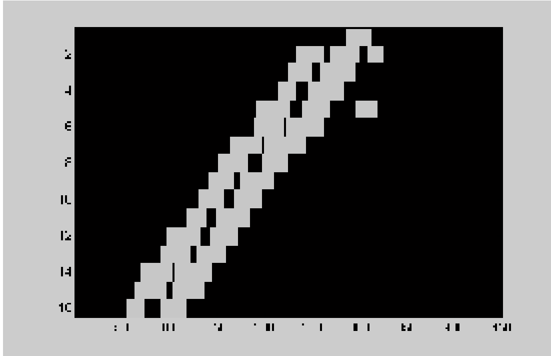

Fig 7*: Actual image of MFL after segmentation*

4. Quantitative recognition of defect parameter

Besides the defect, signs of segmentation from the Magnetic Flux Leakage image usually include the ring welding line, the straight welding line, the valve, and the bends and so on, as the width and length parameter of these signs has obvious characteristics, the defect and the signs area can be separated according to these characteristics.
The pipeline defect information we want to know mainly includes the position, the depth, the length, the width and so on. After the segmentation, positional information and the width、 length of the defect can be known through computation the parameters of the defect image. But the depth information of defect cannot obtain from the M F L image. Figure 8 shows a group of same depths, different length detects axial stray field simulation signals. Obviously, the scope of the Magnetic Flux Leakage signals not only to be decided by the defect ´ s depth, but also decided by defect ´ s shape or other factors. Therefore the defect depth and the scope of Magnetic Flux Leakage signal have the direct relationship, but is not one kind of linear relations. It ´ s very difficult to obtain the precise depth information of defects by the scope of defects ´ signal directly.

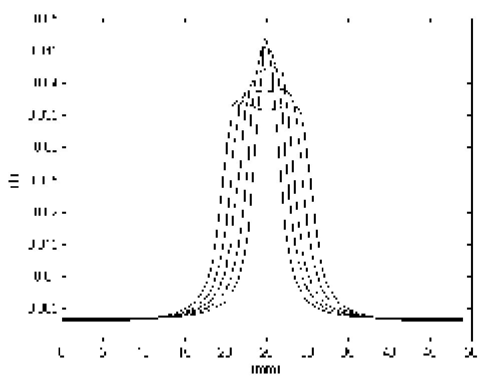

Fig 8*: Axial stray field simulation signal of same depth, different width detects*

In no-damages Inspection domain, the research on defect recognition and reconstruction technology which based on neural network has made some progress as the artificial neural network has non-linear mapping, auto-adapted study abilities. These research give us great inspiration that the precise length and depth information of detects can be obtained by the neural network which has been trained.

4.1 Quantitative recognition of defect parameter which based on BP neural network the MFL image segmentation

The BP neural network is refers to multilayer forward neural network which based on error reverse dissemination algorithm, it has become the most widespread neural network at present. In the experiment, we select three layer BP neural networks, the neuron transfer function is the Sigmoid differentiable function, the outputs neuron use the Purlin linearity transfer function. The number of input level nodes is 140, take the actual Inspection data after preprocess as the input; there are 2 output nodes– depth and length of detect. Because the usual BP neural network algorithm has some shortcomings, such as the convergence rate is slow, easy to fall into partial minimum and so on, so we use its improvement algorithm Levenberg-Marquardt algorithm.

The neural network sample data is obtained from the manual manufacture defect Inspection. Altogether has manufactured 45 different parameters defects. The defects´ shape is rectangle and circular. Use the radial and axial MFL signal of the recognition date as the inputs of BP neural network, the number of training times is 3,000. The recognition result see table 1. Obviously the relative error of recognition result which based on BP network is below 10%, relative error of minority recognition result(for example 5 defects) is bigger, but the absolute error is very small, does not surpass 1mm, this completely conforms to the requirement of actual inspection.

4.2 Quantitative recognition of the Pipeline defects which based on the neural network after data fusion

In the MFL inspection, All axial and radial direction MFL signals reflect the defect´s position, the size, the degree and so on, and the same information had stress respectively, The axial signal has reflected more depth information of the defect, but the radial direction signal had reflected more shape information, the data fusion of axial and radial direction signals, has reflected the comprehensive information of the MFL. In this article, the weighted averages method (for example type 6) and auto-adapted weighted averages method (for example type 7) are used to fuse the radial and axial MFL inspection data. Trains the BP neural network with the fusion data, the number of network training times is 3,000. The recognition result see Table 2, obviously, the BP neural network´s recognition precision has been enhanced after the data fusion, moreover recognition results´ reliable increase. The recognition result which use the weighted averages method is better than that use the auto-adapted weighted averages method.

$$\bar{x} = \frac{x_a}{2} + \frac{x_r}{2} \qquad (6)$$

x_a Expressed axial MFL signal, x_r expressed the radial direction MFL signal.

$$x = \sqrt{x_a^2 + x_r^2} \qquad (7)$$

5 Conclusions

After to be preprocessed, such as elimination of noise, image enhancement and so on, pipeline MFL (Magnetic Flux Leakage) image will be segmented with max entropy algorithm and dilation algorithm, the position, width, etc. of defect can be calculated according to defect image. Quantitative recognition of the length, the depth of defect can be realized by use the BP neural network, the recognition result error is smaller than 10%. After use two methods ,which is the weighted average method and the auto-adapted weighted average method ,to fuse the radial and axial MFL signals, the BP neural network recognition result´s precision and reliability received improvement.

6 References

[1] ▪ 理践等 智能化管道漏磁▪ ▪ 装置的研究 ▪ [▪ J], 2002, 24（3）: 100-102.

[2] W.Tham, S.Wooley. The detection and segmentation of pipeline inspection features for diagnostically lossless data compression IST/SPIE Electronic Imaging 2001 21-26 January 2001, San Jose, California, USA

[3] K.Hwang, S. Mandayam, S.S. Udpa et al,Application of Wavelet Basis Function Neural Networks to NDE, 0-7803-3636-4/97 1997 IEEE

[4] Pradeep Ramuhalli, Muhammad Afzal, Kyung-Tae Hwang et al,A Feedback Neural Network Approach for Electromagnetic NDE Signal Inversion, Electromagnetic Nondestructive Evaluation, IOS Press,2000

[5] ▪ 涛，王太勇，李清等 基于特征量和神▪ 网▪ 的▪ 管缺陷▪，▪▪ [J] 模型 Vol . 39 No.9, 2004,50– 53.

Table1: Quantitative recognition result of defects based on BP neural network

Defects serial number	defects parameter		Radial direction signal		Axial signal	
			Recognition result	Relative error	Recognition result	Relative error
1	Length(cm)	8.5	9.0887	6.93%	7.9821	-6.81%
	Depth(mm)	3.5	3.8417	9.76%	3.2014	-8.5%
2	Length(cm)	10	9.4779	-5.22%	11.444	11.44%
	Depth(mm)	5	4.6718	-6.56%	5.3536	7.07%
3	Length(cm)	4.5	4.1358	-8.09%	4.4777	-0.5%
	Depth(mm)	3.5	3.51	0.28%	3.7151	6.15%
4	Length(cm)	4.5	4.4117	-1.96%	4.3695	-2.9%
	Depth(mm)	2	1.298	-35.1%	2.6183	30.91%
5	Length(cm)	7.5	6.2606	-16.52%	7.1906	-4.12%
	Depth(mm)	2	2.9525	47.62%	1.9809	-0.96%

Table 2: BP neural network recognition result after data fusion

Defects serial number	Defects parameter		Weighted average		Auto-adapted weighted average	
			Recognition result	Relative error	Recognition result	Relative error
1	Length(cm)	8.5	8.6596	1.88%	8.712	2.59%
	Depth(mm)	3.5	3.365	-3.86%	3.4462	-1.53%
2	Length (cm)	10	10.126	1.26%	8.9763	-10.24%
	Depth (mm)	5	4.5332	-9.34%	4.3831	-12.34%
3	Length (cm)	4.5	4.7359	5.24%	3.8114	-15.3%
	Depth (mm)	3.5	3.2409	-7.4%	3.8366	9.62%
4	Length (cm)	4.5	4.4907	-0.21%	5.2147	15.88%
	Depth (mm)	2	2.1763	8.82%	1.6995	-15.03%
5	Length (cm)	7.5	7.0848	-5.54%	6.7323	-10.24%
	Depth (mm)	2	1.7854	-10.73%	2.1067	5.34%