[Regular Paper]

Improved Ultrasonic Offshore Oil Pipeline Thickness Accurate Detection Using Hilbert-Huang Transform and Elman Neural Network

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Pipeline flaw detection and safety evaluation are very important because of internal corrosion usually caused by the presence of the water (salty or not), and external damage by anchors or other equipment. Any possibility of leakage must be detected before leakage occurs and preventive action should be taken to avoid losses of oil and ecological disasters. The ultrasonic method is the most commonly used to detect material loss and/or cracking of the pipeline. The ultrasonic intelligent pig is used to detect the pipeline thickness, but the complicated offshore and pipeline environment, especially the variable sensor lift-off (distance between ultrasonic probe and pipeline wall under detection), reduces the accuracy of pipeline thickness measurement. The Hilbert-Huang transform was used to extract the signal features, then the Elman neural network applied to eliminate the effect of lift-off variation to improve the flaw detection accuracy. Experiments showed that the accuracy of detected time of flight between the transmitted pulse and echo from the pipeline wall as well as the thickness of the pipeline wall were clearly improved.

Keywords
Elman neural network, Hilbert-Huang transform, Feature extraction, Thickness detection

1. Introduction

Offshore oil pipelines are built with carbon steel pipes, and can extend to uninterrupted lengths of hundreds of kilometers[1]. These steel pipes are prone to internal corrosion, usually caused by the presence of water (salty or not), and external damage by anchors and other equipment. More and more pipelines have been buried with the increase in offshore oil and gas exploitation in China. Therefore, inspection and maintenance methods for the pipelines are urgently needed and offshore oil pipeline safety evaluation is very important in China.

Ultrasonic inspection is the most commonly used method to detect material loss and/or cracking of the pipeline[2]. Ultrasonic inspection provides quantitative results such as extension and depth of the defect with accuracy of mm, because of the pulse-echo mode with rather high repetition frequency. The ultrasonic sensor transmits the ultrasonic pulse and then receives the echo reflected from the specimen. The echo signal at the flaw is highly complex due to the interference of multiple signals with random amplitude and phase. Therefore, one of the most difficult tasks faced by the data interpreter is the recognition of suspect flaw regions in the ultrasonic signals.

The ultrasonic intelligent detection device is usually called the ultrasonic pig. The ultrasonic intelligent pig has six components: driver robot, system controller, power supply, ultrasonic measuring head, data acquisition and processing device, and position tracer. **Figure 1** shows the simplified structure of the ultrasonic inspection device.

In recent years, neural networks have been widely used in science, engineering, medicine, and economics because of their powerful pattern recognition ability. The application of neural networks to nondestructive testing focuses mainly on recognizing and classifying the presence of flaws in the material. The classification of the flaws has been discussed much more extensively than the recognition of flaws[3)~5),9)]. The ART2 network and fuzzy neural network have been used to

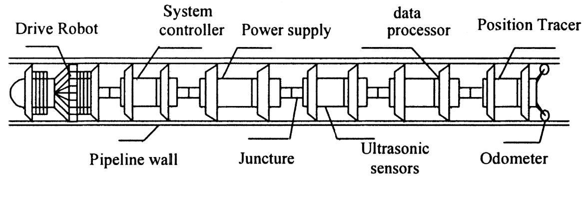

Fig. 1 Simplified Structure of the Ultrasonic Inspection Device

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classify the flaws[6].

The main parameter for evaluating pipeline flaws is the thickness of the pipeline. In theory, if the time interval between the transmitted pulse and the echo signal from the pipeline wall is known, the thickness of the pipeline can be calculated easily. However, in the real complex detection environment, the lift-off value (the distance between the ultrasonic sensor and the pipeline inner wall) is changed for every detection location. There are many complex reasons for the variation in the lift-off value. For example, vibration of the detection equipment and wax or rust adhering to the pipeline wall can reduce the amplitude of the ultrasonic echo. If the defect is smaller than the ultrasonic sensor diameter, the echo signal is difficult to analyse at the edge of the defect. These factors all greatly influence the detection accuracy. The lift-off value is showed in **Fig. 2**. To eliminate the effect of the lift-off value, we must find a reasonable method to resolve this problem.

The present study applied the Elman neural network to detect the pipeline depth by eliminating the influence of the lift-off value to increase the detection accuracy. The Elman neural network[7] is a partial recurrent network model first used in speech processing[8], and has certain unique dynamic characteristics over static neural networks, such as multilayer perceptions and radial-basis function networks.

2. Proposed Method

Figure 3 shows the scheme of the pipeline thickness detection. The ultrasonic signal is first processed by empirical mode decomposition and the external features calculated to extract the main features. Then some useful features are selected. Finally, the features are combined as the inputs of the Elman neural network.

2.1. Feature Extraction of the Pipeline Ultrasonic Signal

Figure 4 shows an example ultrasonic signal which includes the transmitted pulse and flaw echo signal from the pipeline. Using all ultrasonic data as the input of the Elman neural network will require too much operating time, so the main features are extracted from the ultrasonic echo signal.

Flaw recognition depends on the selected features of the echo signal. Features can be extracted by many approaches. We selected features such as time of flight information, maximum amplitude of the echo, echo energy, and frequency information[9]. **Figure 5** shows the echo signal external features.

Good feature selection is the essential step in flaw recognition. The feature selection algorithms use split spectrum processing and wavelet transform. Split Spectrum processing is used to create frequency-diverse signal features[10]. Wavelet transform is used to obtain the scale-time information features[11].

This study used the Hilbert-Huang transform to obtain instantaneous frequency information features. The Hilbert-Huang transform, or empirical mode decomposition (EMD), was recently proposed as a signal processing technique suitable for nonlinear and nonstationary series[12]. The Hilbert-Huang transform mainly includes two steps, empirical mode decomposition in which complicated data are decomposed into a finite

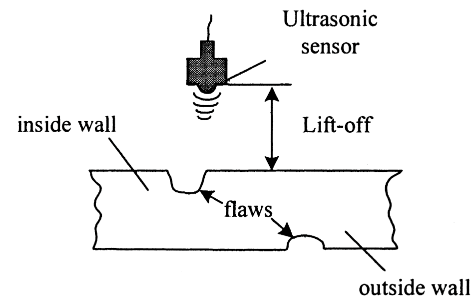

Fig. 2 Explanation of the Lift-off Value

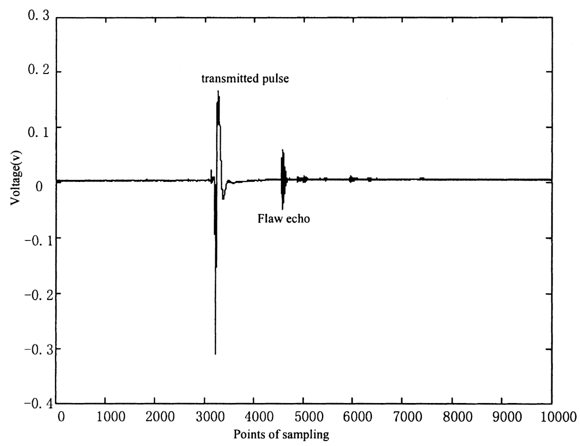

Fig. 4 Example Ultrasonic Signal of the Pipeline

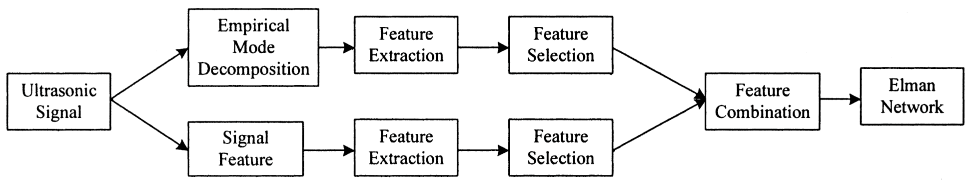

Fig. 3 Scheme of Flaw Recognition

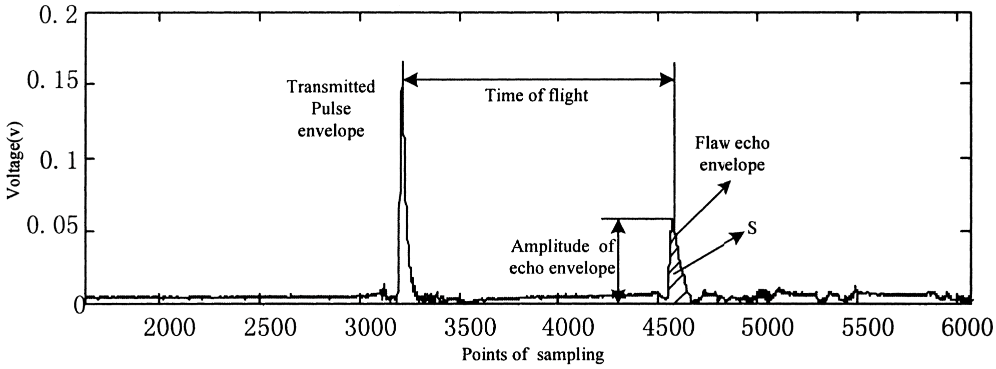

Fig. 5 Flaw Signal External Features

number of component, called intrinsic mode functions (IMF), and application of the Hilbert transformation to the IMFs to obtain the instantaneous frequency. Because the IMF instantaneous frequency is narrow band, the mean of all IMF instantaneous frequencies was calculated as the inputs of the Elman neural network.

The algorithm of empirical mode decomposition can be summarized as follows[12]:

(1) Identify all extrema of $x(n)$.
(2) Interpolate (here we use spline interpolation) between minima (resp. maxima), ending up with some "envelope" $e_{\min}(n)$ (resp. $e_{\max}(n)$).
(3) Calculate the average $m(n) = (e_{\min}(n) + e_{\max}(n))/2$.
(4) Extract the detail $d(n) = x(n) - m(n)$.
(5) Iterate on the residue $r(n)$.

In practice, the above procedure has to be refined by a sifting process which amounts to first iterating steps (1)-(4) on the detail signal $d(n)$, until it can be considered as zero-mean according to termination criterion SD (standard deviation, calculated from two consecutive sifting results[12],

$$SD = \sum_{n=1}^{N}\left[\frac{\left|d_{j(k-1)}(n) - d_{jk}(n)\right|^2}{d_{j(k-1)}^2(n)}\right] \le \xi$$

N is the total data length and ξ is a threshold set in advance (we here set $\xi = 0.25$). $d_{jk}(n)$ is the kth sifting result of jth mode. Once this is achieved, $d_{jk}(n)$ is considered as the jth effective mode $c_j(n)$, the corresponding residue is calculated and step (5) is applied.

IMFs can be obtained after empirical mode decomposition. The Hilbert transform is applied to each IMF, and the instantaneous frequency of each IMF calculated. The detail of the calculation method is given elsewhere[12].

2. 2. Elman Neural Network

Figure 6 shows the basic Elman neural network which contains four layers: input layer, hidden layer, context layer, and output layer. $x_i(k)$ ($i = 1, \cdots, m$) is the inputs of the Elman neural network. $y_j(k)$ ($j = 1, \cdots, n$) is the outputs of the Elman neural network. $h_l(k)$ ($l = 1, \cdots, r$) is the hidden of the Elman neural network. $c_l(k)$ ($l = 1, \cdots, r$) is the output of the context node l.

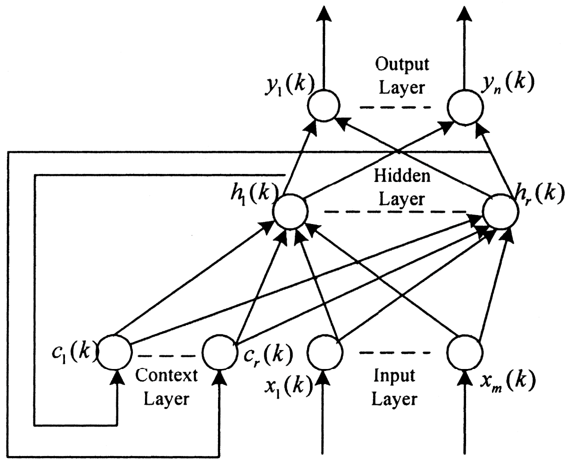

Fig. 6 Elman Neural Network

The outputs in each layer can be given by

$$h_l(k) = F\left(\sum_{i=1}^{m} w1_{i,j} x_i(k) + \sum_{i=1}^{r} w2_{i,j} c_i(k)\right)$$

$$c_i(k) = h_i(k-1)$$

$$y_j(k) = G\left(\sum_{i=1}^{r} w3_{i,j} x_i(k)\right)$$

where, F and G are the output functions of the hidden layer and output layer. $w1_{i,j}$ is the weight from the input layer to the hidden layer. $w2_{i,j}$ is the weight from the context layer to the hidden layer. $w3_{i,j}$ is the weight from the hidden layer to the output layer. The training algorithm for the Elman neural network is the standard back-propagation (BP) learning algorithm[13].

2. 3. Process of the Algorithm

In summary, the algorithm can be implemented by the following procedure:

(1) Calculate the external features of the flaw signal,

such as time of flight information, maximum amplitude of the echo, and echo energy,
(2) Decompose the flaw signal with empirical mode decomposition to obtain the IMF.
(3) Apply the Hilbert-Huang transform to every IMF to obtain the instantaneous frequency.
(4) Calculate the mean of the instantaneous frequency of every IMF.
(5) Select the main features as inputs of the Elman neural network.
(6) Train the network.
(7) Test the network.

3. Experimental Results

In this experiment, the diameter of the pipeline was 219 mm, and the thickness of the pipeline was 12 mm. Rectangular flaws made in the laboratory (**Fig. 7**) were detected using the proposed algorithm to judge the thickness of the pipeline. **Table 1** shows the partial size of the artificial pipeline rectangular flaws with length from 6 to 15 mm, width from 6 to 15 mm, depth from 0.8 to 5 mm. The total was 15 rectangular flaws. Experimental pulse-echo signals were obtained using a circular ultrasonic probe, using longitudinal wave, 5 MHz center frequency and 6 mm diameter. Sampling frequency was 100 MHz.

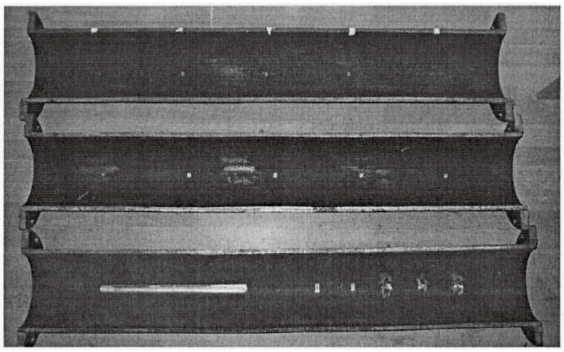

Fig. 7 Partial Flaws Made in the Laboratory

The echo signal at the artificial flaws was detected many times. Forty samples were obtained. The flaw depth was from 1.5 to 5 mm. We selected 30 samples as training sample sets, and 10 samples as testing sets. The training sample sets included all flaw depths.

The inputs of the Elman neural network were time of flight information, maximum amplitude of the echo, echo energy, and four means of instantaneous frequency. The node number of the hidden layer was twelve. The node number of the output layer was one. The output layer was the wall thickness.

Table 2 shows the results. The relative error of calculating value directly between transmitted pulse and flaw echo was bigger than that of the recognition value using the neural network. Detection precision was enhanced for various reasons. When the inspection device is crawling in the pipeline, the vibration of the detection equipment and wax or rust adhering to the pipeline wall can lead to reduce the amplitude of the ultrasonic echo, so it is difficult to calculate the wall thickness according to the ultrasonic echo. If the size of defect is smaller than the size of the ultrasonic sensor diameter, the echo signals at the edge of the flaw may overlap, so we can use Hilbert-Huang transform to separate these overlapped echo signals[14]. Then, we identified features of the echo signal as training inputs for the neural network. The proposed method is better than the method of calculating value between echoes.

4. Conclusion

The Hilbert-Huang transform was used to extract the instantaneous frequency features, then the Elman neural network applied to train features for the pipeline thickness. With the proposed algorithm, the effect of the

Table 1 Partial Size of Artificial Pipeline Defects

Flaw number	Pipe number	Length [mm]	Width [mm]	Depth [mm]	Gradient [°]	Shape
1	1#	6	6	0.8	90	rectangle
2	2#	8	6	1.5	90	rectangle
3	2#	10	10	3	90	rectangle
4	3#	15	10	4.5	90	rectangle

Table 2 Comparison of Results between Two Different Methods

Data analysis number	Real value [mm]	Calculating value between echoes [mm]	Relative error [%]	Recognition value [mm]	Relative error [%]
1	11.2	10.4	7.2	10.8	3.5
2	10.5	9.8	6.6	10.1	3.8
3	9.0	8.7	3.7	8.7	3.3
4	8.0	7.5	6.2	7.7	3.7

lift-off value was greatly reduced and the detection precision enhanced. In fact, the number of the experiments was not sufficient because of the limits of the experimental condition. The flaws were only rectangular, and the number of the flaws was limit. The number of experiments should be much greater, and all shapes of flaws included to improve the accuracy of the method.

Acknowledgments

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References

1) Weisweiler, F. J., Sergeev, G. N., "Non-destructive testing of large-diameter pipe for oil and gas transmission lines," Weinheim: VCH, (1987).
2) Okamoto Jr., J., Adamowski, J. C., Tsuzuki, M. S. G., Buiochi, F., Camerini, C. S., "Mechatronics," Vol. 9, Elsevier Science, Amsterdam (1999), p. 731-743.
3) Chen, C. H., Lee, G. G., IEEE Ultrasonics Symposium, 1993, p. 493-496.
4) Fiorillo, A. S., D'Angelo, G., IEEE Ultrasonics Symposium, 2002, p. 781-784.
5) McGrail, A. J., AucMand, D. W., Varlow, B. R., IEEE International Symposium on Electrical Insulation, 1994, p. 22-24.
6) Solis, M., Benitez-Perez, H., Rubio, E., Medina, L., Moreno Hernandez, E. R., IEEE Ultrasonics Symposium, 2001, p. 679-682.
7) Elman, J., *Cognitive Science*, **14**, 179 (1990).
8) Cheng, Y., Qi, W., Cai, W., Proceedings of 1st International Conference on Machine Learning and Cybernetics, 2002, p. 637-640.
9) Ait Oufroukh, N., Christian, B., Colle, E., Proceedings of IEEE, 2002, vol. 2, p. 1329-1334.
10) Sun, H. C., Saniie, J., IEEE Ultrasonics Symposium, 1998, p. 855-858.
11) Solis, M., Benitez, H., Medina, L., IEEE Ultrasonics Symposium, 2002, p. 841-844.
12) Huang, N. E., Shen, Z., Long, S. R. *et al*., Proc. R. Soc. Lond. A, 1998, p. 903-995.
13) Zeng, F., Chen, Y., Wu, J., IEEE Int'l Conf. Neural Networks and Signal Processing, China, 2003, p. 100-103.
14) Chen, T.-L., Que, P.-W., Zhang, Q., Liu, Q.-K., *Review of Scientific Instruments*, **76**, 085109 (2005).

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要　旨

Hilbert-Huang 変換と Elman ニューラルネットワークを用いた海洋パイプライン肉厚の超音波による精密検知

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海洋パイプラインの維持管理においてラインの探傷およびその安全性の評価は非常に重要な項目である。パイプライン内面は水の存在により腐食を受け，一方，外面はアンカー等による機械的損傷を受ける傾向がある。輸送原油の逸失および環境破壊を避けるためにパイプラインの漏洩が生じる前にその漏洩の可能性のある部位を正確に検知する必要がある。パイプラインのダメージを探る方法として超音波探傷が一般的に広く行われているが，その肉厚測定に超音波インテリジェントピグを使う場合，複雑な海底地形およびパイプライン敷設環境のためパイプラインの壁面と超音波測定用プローブが離れてしまうセンサーリフトオフ現象が生じることがあり，この場合には肉厚の正確な測定が困難となることがある。このリフトオフ問題に対応するために超音波信号形状の抽出に Hilbert-Huang 変換を使用するとともにリフトオフの種々の影響を抑えるために Elman ニューラルネットワーク手法を適用することにより，精密な超音波検知結果が得られることが本検討により示唆された。

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