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The Leak Detection of Heating Pipe Based on Multi-Scale Correlation Algorithm of Wavelet

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Abstract: Timely detection and high positioning accurate of leakage signals are the guarantee to the safe transport of heating pipeline, which can reduce economic losses and improve heating quality. In order to detect leaks timely and accurately, this paper presents a method that multi-scale correlation algorithm of wavelet to analyze the singular values by monitoring infrasonic signal. Combining the improved high-frequency coefficient domain algorithm of wavelet with multi-scale cross-correlation algorithm, the method deals with signals by cross-correlation analysis layer by layer based on the multi-scale of wavelet. By weighting in the frequency domain and whitening the signals, the signal to noise ratio can be improved and singular values may be detected accurately. Experimental results show that the algorithm has a better effect of positioning and improve the positioning accuracy of leak detection of pipeline. *Copyright © 2013 IFSA.*

Keywords: Wavelet decomposition, Multi-scale cross-correlation, Infrasound signal, Pipeline leak, Positioning accuracy.

1. Introduction

Due to the development of the network distribution of heating pipe and the increasing of environmental corrosion factors inside and outside of the pipe, leakage accident occurred frequently and result from which we may suffer economic losses and environmental damage and also a low quality of life. So accurate positioning and dealing with fault in time are the guarantee to heating safely. The methods of leak detection can be divided into detection inside of pipe [1] and detection outside of the pipe [2]. Using ultrasonic, magnetic flux, video and other technologies by placing the detection equipment into the pipe, the detection inside of pipe can only detect intermittently, because of which it is easy to happen that congestion and outage and the cost is high. With the rapid development of information and modern control theory, outside of the pipe detection has become a hot research. Usually, the method includes balance method [3], real-time model method [4] and transient flow detection method [5], etc. Generally, most of indirect detection methods often detect when the leak has happened, so we can not find leaks promptly and accurately, that is to say, only when a large leak occurs, can we found it. Among most methods of detecting leaks in pipeline, infrasound sensors and optical sensors may be the trend in the future. Because the signals received from them have a high accuracy and a strong anti-interference ability. Combined with intelligent detection algorithm, they can achieve detection and location of pipeline leak.

Called as Mathematical microscope, wavelet analysis becomes a good tool of time-frequency analysis [6], which can filter noise, detect singular value and extract feature. By identifying mutations of leakage signal and filtering signal, detection accuracy of pipeline can be improved. Multi-scale transform of wavelet [7] can highlight local maximum of wavelet coefficients and help to extract singularity characteristic of the leak signal in pipe. The principle of cross-correlation analysis [8] is analyzing the infrasound signals that received from sensors on the both ends of pipe. When the values of cross-correlation function have significantly changed, there is a leak occurs. According to the position formula, we can know the leak point. The method does not need to establish pipeline mathematical model and easy to calculate. In this paper, we detect leakage signal of heating pipeline by multi-scale correlation algorithm of wavelet.

2. Wavelet Reconstruction Algorithm Based on Improved High Frequency Coefficients of Wavelet

2.1. Wavelet Decomposition Algorithm

Wavelet decomposition [9] of infrasonic signal is carried out based on some certain conditions, and the condition need to contain the information of signal [10]. Generally, assuming that decomposition can be achieved when the signal meet the condition that f is similar to $\mathrm{f_j}$ and $\mathrm{f_j}$ is contained in V_j, where V_j is determined by the sampling frequency and multi-scale characteristics. And integral can be done to the function space used in this method ($L^1(R)$) in the range of real numbers. Therefore, when the function meets the condition that $\mathrm{f(t)}$ is contained in $L^2(R)$, we can get that:

$$f(t)=\sum_{j,k\in Z}<f,\psi_{j,k}>\psi_{j,k}(t), \tag{1}$$

Especially for any subspace V_j in $L^2(R)$:

$$\begin{aligned}V_j&=V_{j-1}\oplus W_{j-1}\\&=V_{j-2}\oplus W_{j-2}\oplus W_{j-1}\\&=\cdots\\&=V_M\oplus W_M\oplus W_{M+1}\oplus\cdots\oplus W_{j-1}(M>j)\end{aligned}, \tag{2}$$

So, any function f_j in V_j can be shown with multi-scale resolution as follows:

$$\begin{aligned}f_j&=f_{j-1}+d_{j-1}\\&=f_{j-2}+d_{j-2}+d_{j-1}\\&=\cdots\\&=f_M+d_M+d_{M+1}+\cdots+d_{j-1}\end{aligned}, \tag{3}$$

where

$$f_l(t)=\sum_k c_k^l\phi_{l,k}(t)\in V_l, l=M,\cdots,j, \tag{4}$$

$$d_l(t)=\sum_k d_k^l\psi_{l,k}(t)\in W_l, l=M,\cdots,j-1, \tag{5}$$

and $f_M(t)$ is the low-frequency portion which comes from decomposition of f_j, $\mathrm{d}_l(t)$ is the high-frequency components in the multi-scale resolution and l is the data from M to $j-1$. Low-frequency signal can be seen as the whole signal and high-frequency signal represents the specific details of signal.

2.2. The Wavelet Reconstruction Algorithm that Improves Wavelet Coefficients

Using wavelet transform, a set of high-frequency coefficients (that is $\{d_{j-1},d_{j-2},\cdots,d_{M+1},d_M\}$) can be obtained [11]. Because the difference between neighboring wavelet coefficients is small, it has been verified that the detection effect of singular value is not ideal. So we present an improved method in this paper. In the method, exponentiation that based on e can be operated to wavelet coefficients one by one [12]. And then a new set of frequency coefficients can be obtained, which is shown as the formula (6):

$$\begin{aligned}&\{\tilde{\mathrm{d}}'_{\mathrm{j-1}},\tilde{\mathrm{d}}'_{\mathrm{j-2}},\ldots,\tilde{\mathrm{d}}'_{\mathrm{M+1}},\tilde{\mathrm{d}}'_{\mathrm{M}}\}\\&=\{e^{d_{j-1}},e^{d_{j-2}},\ldots,e^{d_{M+1}},e^{d_M}\}\end{aligned}, \tag{6}$$

Then, original signal can be restored by wavelet reconstruction algorithm, shown as formula (7):

$$\begin{aligned}&\{\tilde{\mathrm{d}}'_{\mathrm{j-1}},\tilde{\mathrm{d}}'_{\mathrm{j-2}},\ldots,\tilde{\mathrm{d}}'_{\mathrm{M+1}},\tilde{\mathrm{d}}'_{\mathrm{M}}\}\\&=\{e^{d_{j-1}},e^{d_{j-2}},\ldots,e^{d_{M+1}},e^{d_M}\}\end{aligned}, \tag{7}$$

After analyzing, db6 wavelet is chosen to be the optimal wavelet to analyze the signal in multi-scale. Shown as Fig. 1 that a6 stand for low frequency coefficients and d1 to d6 are high-frequency coefficients and all of which are obtained by wavelet decomposition. According to high-frequency coefficients of wavelet decomposition, simulation result of multi-scale analysis to the signal is shown in Fig. 2.

Db6 wavelet is chosen to make multi-scale analysis of signals. In general, the more decomposition level, the more conducive to separate signal from noise. But for reconstruction, more decomposition level can bring bigger reconstruction error and greater distortion. In this paper, db6 wavelet is chosen to make six layers wavelet decomposition to original signal. The signal that from the first layer to the sixth layer is detail signal and also high-frequency sequence, and the sixth layer approximation signal is low-frequency sequence. Seen from Fig. 1, when the signal is not analyzed by wavelet coefficient domain transform, the singular value of infrasound signal at different scales is not obvious. Thus, we can not determine the time domain position that corresponding to mutations. Shown as Fig. 2, dealing with signal by wavelet coefficient domain transform, high-frequency coefficients in the d1 layer have an obvious peak, and sampling points that corresponded is the 112th point. And then we can not determine whether the leaks occur. By using the improved method, the range of peak is more focused and the positioning of the point of mutations is more precisely. According to sampling frequency, time domain position can be calculated.

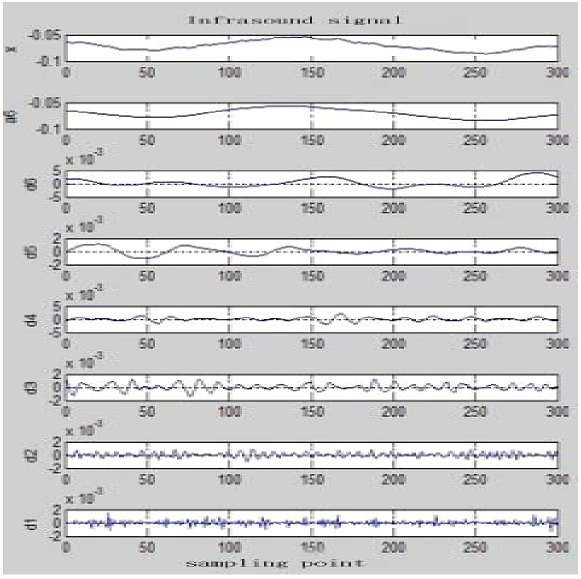

Fig. 1. Result of wavelet analysis.

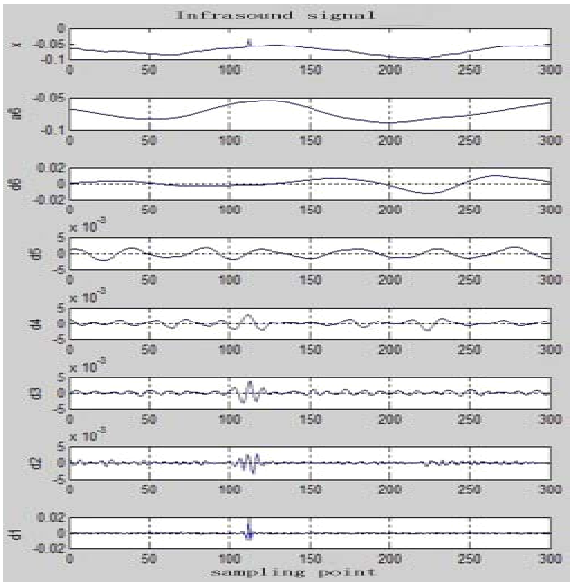

Fig. 2. The analysis in high-frequency coefficient domain with wavelet decomposition.

3. Wavelet Multi-scale Cross-correlation Analysis Algorithm

Usually, it is difficult to detect the true position and the type of singular values in single scale [13]. Only when there are extreme points in all multi-scale, the location of mutations can be determined accurately. So the method that cross-correlation analysis based on multi-scale is proposed to detect singular value, and by which we can reduce errors and improve accuracy of leakage detection.

3.1. Multi-Scale Decomposition System

Assuming that the state equations and measurement equations in i scale are obtained, and system model [14] of pipeline is shown as follow:

$$x_v(i,k+1) = F_v(i)x_v(i,k) + w_v(i,k), \tag{8}$$

$$w_v(i,k) \sim N(0, Q_v(i,k)), \tag{9}$$

$$z_v(i,k+1) = H_v(i)x_v(i,k) + v_v(i,k), \tag{10}$$

$$v_v(i,k) \sim N(0, R_v(i,k)), \tag{11}$$

Formula (8) is decomposed by wavelet transform with the scale from i to $i-1$, and the results are shown as follow:

$$\begin{aligned} &x_v^i(i-1,k+1) \\ &= F_v^i(i-1)x_v^i(i-1,k) + w_v^i(i-1,k) \end{aligned}, \tag{12}$$

$$w_v^i(i-1,k) \sim N(0, Q_v^i(i-1,k)), \tag{13}$$

where the results are obtained by decomposition in the scale i:

$$F_v^i(i-1) = F_v(i)F_v(i), \tag{14}$$

$$\begin{aligned} Q_v^i(i-1,k) &= F_v(i)\sum_l h^2(l)Q_v(i,2k-l)F_v^T(i) \\ &+ \sum_l h^2(l)Q_v(i,2k+1-l) \end{aligned}, \tag{15}$$

Formula (10) is decomposed by wavelet transform from scale i to $i-1$, and the results are shown as follow:

$$\begin{aligned} &z_v^i(i-1,k) \\ &= H_v^i(i-1)x_v^i(i-1) + v_v^i(i-1,k) \end{aligned}, \tag{16}$$

$$v_v^i(i-1,k) \sim N(0, R_v^i(i-1,k)), \tag{17}$$

where

$$C_v^i(i-1) = C_v(i), \tag{18}$$

$$R_v^i(i-1,k) = \sum_l h^2(l) R_v(i, 2k-l), \tag{19}$$

3.2. Multi-scale Cross-correlation Analysis

The step of Multi-scale cross-correlation analysis algorithm is as follows:

A. In this paper, $x_1(t)$ and $x_2(t)$ are two group of data that collected in a certain time in the field. In order to describe the dynamic system of multi-scale decomposition algorithm, assuming that state equation and measurement equation analysis can be done in the i scale. Due to the influence of sampling frequency, the collected data is seen as leakage signal in the finest scale, here the finest scale take $N = 5$;

B. Doing wavelet decomposition in $i = 5$, different dynamic equations can be obtained and we can get smoothed signal.

C. The detail signal in the 5th scale is the difference between the signal to be detected and the smoothed signal. If the detail signal does not include leakage information, it is seen as Gaussian noise which can be filtered. If it does not meet distribution of Gaussian, then the leakage signal is contained and we should detect and locate on the scale, otherwise it will cause positioning errors.

D. If the details of the signal can be filtered out, then the observed data should be continue to do wavelet decomposition until the result meet with the stop condition in the third step or $i = 1$.

E. The detail signals that come from wavelet decomposition are used to do cross-correlation analysis to determine and locate the leak.

F. The measured data is transferred to the host computer and the data will be filtered and correlation calculation will be done in single-scale and multi-scale, MATLAB simulation results are shown in Fig. 3, Fig. 4 and Fig. 5.

The infrasound signal shown in Fig. 3 is collected by sensors which are set on both ends of pipe at the scene. Simulation result of single-scale correlation analysis to the signals that have been filtered is shown in Fig. 4. The detail of the curves in the figure is not obvious and main peak of related is submerged in the background noise, because of which we can not see related main peak. So the effect of infrasound detection is not good. Simulation results of multi-scale cross-correlation analysis is shown in Fig. 5, in which detail of this method is more prominent and there is a clear related peak and signal to noise ratio is improved.

The results of compare of single-scale cross-correlation analysis and multi-scale cross-correlation analysis are shown in Table 1 and the compare of wavelet decomposition algorithm and multi-scale cross-correlation analysis algorithm are shown in Table 2. The results show that the positioning error of multi-scale cross-correlation analysis is significantly lower than the single-scale cross-correlation analysis, and the detection precision of multi-scale cross-correlation analysis is higher than single-scale cross-correlation analysis, and the signal noise ratio (SNR) of multi-scale cross-correlation analysis is superior to the wavelet decomposition algorithm, and the mean square error is higher than wavelet decomposition algorithm.

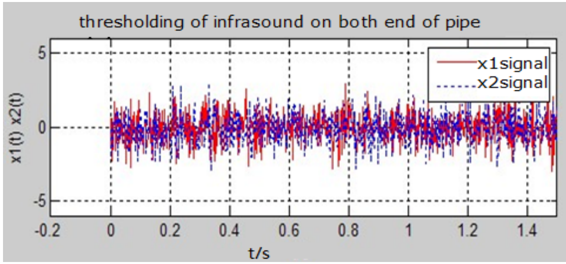

Fig. 3. Infrasound signal.

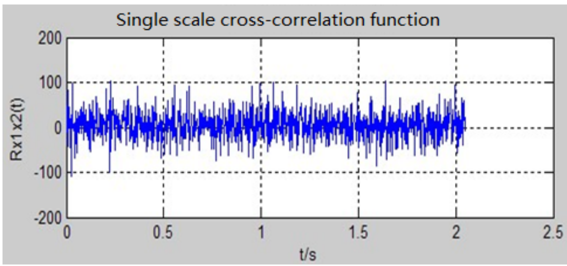

Fig. 4. Single scale cross-correlation analysis.

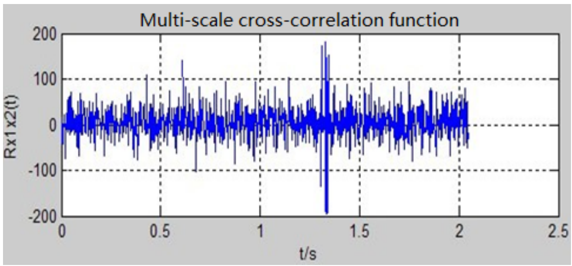

Fig. 5. Multi-scale cross-correlation analyses.

Table 1. Results of compare of single scale with multi-scale cross-correlation analysis.

Positioning error of leak point (%)	1	2	3	4	5
Delay(s)	0.0223	0.119	0.0187	-0.0525	-0.1603
Single-scale cross-correlation analysis	2.14	1.33	2.90	-3.63	-1.84
Multi-scale cross-correlation analysis	0.56	0.29	0.19	-0.31	-0.92

Table 2. Comparing result of multi-scale wavelet decomposition algorithm and Multi-scale cross-correlation analysis algorithms.

Performance index	SNR	MSE
Multi-scale wavelet decomposition algorithm	24.937	1.200
Multi-scale cross-correlation analysis	25.553	1.251

4. The Cross-correlation Time Delay Estimation

4.1. Simulation and Analysis Method of Cross-correlation Time Delay Estimation

When dealing with infrasonic signal with the method of time delay, assuming that the received signals from both ends are seen as $x(n)$, and the number i and number k of signals are shown as follows:

$$x_i(n) = a_i s(n - \tau_i) + w_i(n), \quad (20)$$

$$x_k(n) = a_k s(n - \tau_k) + w_k(n), \quad (21)$$

where $s(n)$ is the infrasound signal, $w_i(n)$ and $w_k(n)$ are Gaussian white noise but no related with each other, $s(n)$ and $w(n)$ are uncorrelated random signals, τ_i and τ_k are the propagation time of $x_i(n)$ and $x_k(n)$, a_i and a_k are attenuation factor.

The cross-correlation functions of $x_i(n)$ and $x_k(n)$ is $R_{ik}(\tau)$:

$$R_{ik}(\tau) = E(x_i(n) x_k(n - \tau)), \quad (22)$$

Analyzing the correlation of signal, we can get that:

$$\begin{aligned} R_{ik}(\tau) &= a_i a_k E(s(n - \tau_i) s(n - \tau_k - \tau)) \\ &= a_i a_k R_s(\tau - (\tau_i - \tau_k)) \end{aligned}, \quad (23)$$

The value of $R_{ik}(\tau)$ is maximum, when τ is equal to $\tau_i - \tau_k$ and τ represents the time delay that is τ_{ik}.

4.2. Spectrum Density of Cross-correlation

When spectral density of cross-correlation with different weighting window do multiply in the frequency domain, error estimation of cross-correlation function can be obtained by IFFT, and by which we can reduce the effect of noise.

Dealing with two signals by FFT, function of cross-correlation spectral density is shown as follow:

$$S_{x1x2}(f) = R_s(f) e^{-j2\pi f D} + S_{mn}(f), \quad (24)$$

where $s(t)$ are the useful signal, $n(t)$ and $m(t)$ are the noise signal, and D is the time difference between leakage signals from sensor on both end of pipe.

$$S_{nn}(f) = R_n(f) = R_m(f) = 0, \quad (25)$$

Time difference of arrival is calculated by cross-correlation function and the cross-spectral density function in frequency domain, we can further reduce the impact of noise to useful signal. Cross-spectral density is weighted and the value is that:

$$A = \frac{1}{\sqrt{S_y}}, \quad (26)$$

IFFT is done to weighted cross-spectral density. The cross-correlation spectral density is shown as follow:

$$\begin{aligned} G(\tau) &= \int_{-\infty}^{+\infty} A S_{x1x2}(f) e^{-j2\pi f \tau} df \\ &= \int_{-\infty}^{+\infty} \frac{S_{x1x2}(f)}{\sqrt{S_{x2}(f)}} e^{-j2\pi f \tau} df \end{aligned}, \quad (27)$$

Time difference between signal spread to the both end of sensors can be calculated by finding the maximum of leakage infrasonic signal.

4.3. Frequency-domain Weighting Analysis

According to cross-correlation algorithm of cross-power spectrum, weighting in the frequency domain can be realized. By whitening the signal and noise, SNR of the signal can be improved. The direct cross-correlation function of two signals can be got according to the inverse transformation of time domain by FFT.

$$R^g_{x1x2}(t) = \int_{-\infty}^{+\infty} A G_{x1x2}(\tau) e^{-j2\pi\tau_t} d\tau, \quad (28)$$

where A is weighted function of cross-correlation, and depending on the specific information of signal and noise, the peak obtained by generalized correlation function of cross-power spectrum can be sharpened according to the different weights of different noises.

4.4. Application of Multi-scale Analysis of Wavelet in Pipeline Leak Detection

1) Process of implementation.

The signal is decomposed into multiple scales, and dealing with two parallel signals by cross-correlation analysis on the single scale, then we can receive the time difference that is Δt and the difference become a set of vectors that are $T = \lfloor \Delta t_1, \Delta t_2, ..., \Delta t_j \rfloor$, where j is the level of the scale of the wavelet decomposition. The accuracy of leak point can be improved by weighting average to the delay estimation on multi-scale.

A. Firstly, we should select the appropriate wavelet, db6 is chosen to analyze and the level of wavelet decomposition is determined.

B. In this part d_j is wavelet coefficient of layers of signal that get from wavelet decomposition. Where j is the data from 1 to N , namely vectors of two wavelet coefficients are shown as follow:

$$dx_1(t)_j = [dx_1(t)_1, dx_1(t)_2, \cdots, dx_1(t)_j], \quad (29)$$

$$dx_2(t)_j = [dx_2(t)_1, dx_2(t)_2, \cdots, dx_2(t)_j], \quad (30)$$

C. N-layer wavelet coefficients are selected from the two signals to make cross-correlation, the result is shown as follow:

$$R_{x_1 x_2}(\tau_i) = E[dx_1(t)_N \, dx_2(t+\tau)_N], \quad (31)$$

A set of vectors of τ_i can be obtained which is named $\tau_i = [\tau_1, \tau_2, \cdots, \tau_N]$.

D. In all scales, maximum of $R_{x_1 x_2}(\tau_i)$ is selected and the time delay that corresponding to the maximum is seen as τ_i, namely $\tau_{i\max}$ is equal to $\tau_{k\max}$, where k is data from 1 to i 。

E. $\tau_{k\max}$ is the sampling time that corresponding to the time when K-layer wavelet coefficients change suddenly, and the time named as T_k.

F. Weighting to T_k and the result is shown as follow:

$$T_{fault} = \sum_{k=1}^{N_c} \zeta_k T_k \Big/ \sum_{k=1}^{N_c} \zeta_k \quad \left(1 \le N_c \le 2^j\right) \quad (32)$$

$$T' = \sum_{k=1}^{N_c} s_k \Big/ k, \quad (33)$$

where T' is the average of the time of mutation, and we know that

$$\zeta_1 : \zeta_2 : \cdots \zeta_{N_c} = \frac{1}{(T_1 - T')^2} : \frac{1}{(T_2 - T')^2} : \cdots : \frac{1}{(T_{N_c} - T')^2}, \quad (34)$$

G. In this part, T' is changed to time delay, namely,

$$\hat{D} = \Delta t_{k\max} = (\tau_{k1\max} - \tau_{k1\max})/f, \quad (35)$$

and where f is the sampling frequency.

2) Analysis of the experimental results.

Simulation is done to multi-scale cross-correlation of wavelet and it is operated to high frequency information of layers by adding weight.

A. In the 6th layer, the high frequency information of signals on the both end are shown in Fig. 6 and Fig. 7. The result of cross-correlation analysis for the signals in this scale is shown in Fig. 8. We can see the time delay from the results and $\Delta t = 0.167$s.

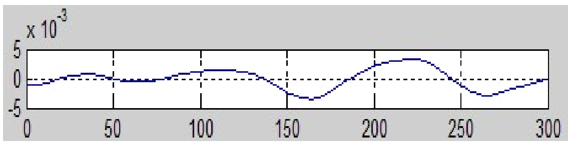

Fig. 6. High frequency information of Db6 on the start side

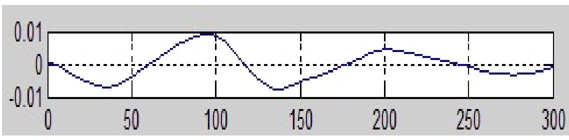

Fig. 7. High frequency information of Db6 on the end side

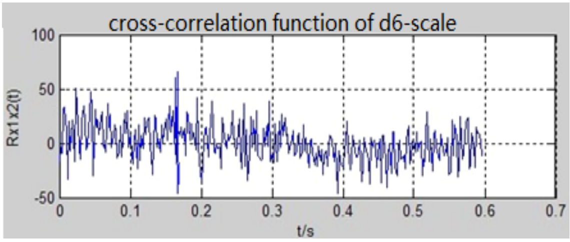

Fig. 8. Cross-correlation function of Db6

B. In the 5th layer, the high frequency information of signals on the both end are shown in Fig. 9 and Fig. 10. The result of cross-correlation analysis for the signals in this scale is shown in Fig. 11. We can see the time delay from the results and $\Delta t = 0.113\text{s}$.

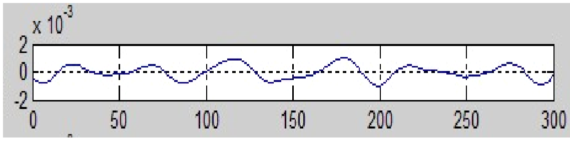

Fig. 9. High frequency information of Db5 on the start side.

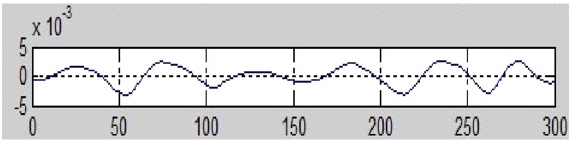

Fig. 10. High frequency information of Db5 on the end side.

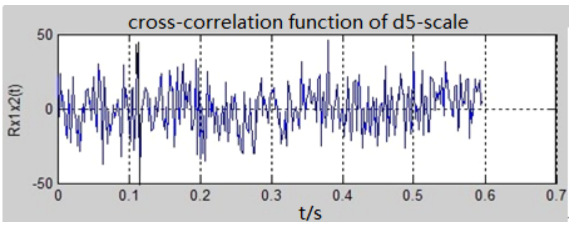

Fig. 11. Cross-correlation function of Db5.

C. In the 4th layer, the high frequency information of signals on the both end are shown in Fig. 12 and Fig. 13. The result of cross-correlation analysis for the signals in this scale is shown in Fig. 14. We can see time delay from the results and $\Delta t = 0.132\text{s}$.

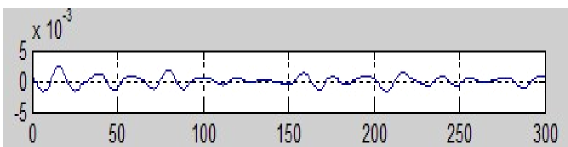

Fig. 12. High frequency information of Db4 on the start side.

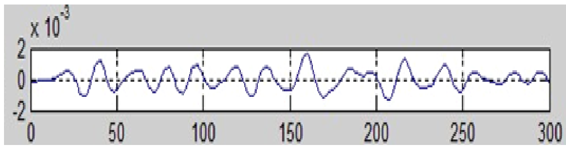

Fig. 13. High frequency information of Db4 on the end side.

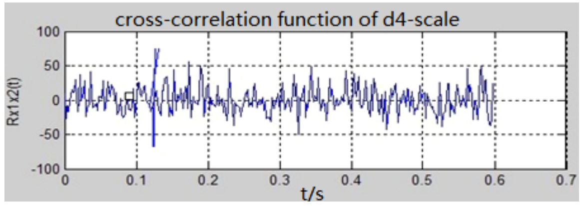

Fig. 14. Cross-correlation function of Db4.

D. In the 3rd layer, the high frequency information of signals on the both end are shown in Fig. 15 and Fig. 16. The result of cross-correlation analysis for the signals in this scale is shown in Fig. 17. We can see time delay from the results and $\Delta t = 0.118\text{s}$.

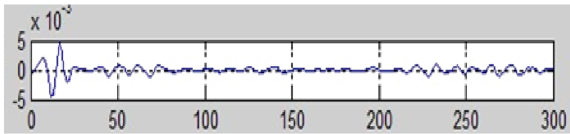

Fig. 15. High frequency information of Db3 on the start side.

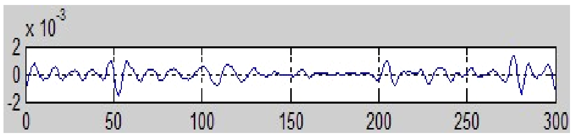

Fig. 16. High frequency information of Db3 on the end side.

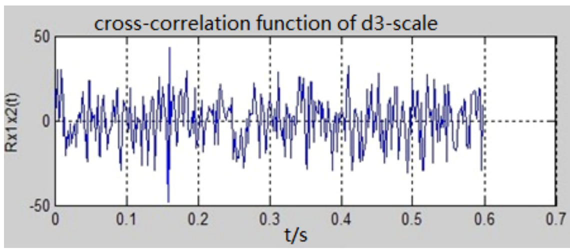

Fig. 17. Cross-correlation function of Db3.

E. In the 2nd layer, the high frequency information of signals on the both end are shown in Fig. 18 and Fig. 19. The result of cross-correlation analysis for the signals in this scale is shown in Fig. 20. We can see the time delay from the results and $\Delta t = 0.022\text{s}$.

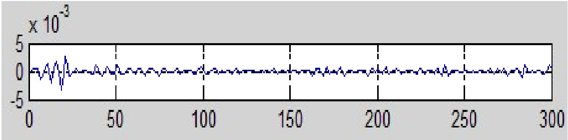

Fig. 18. High frequency information of Db2 on the start side.

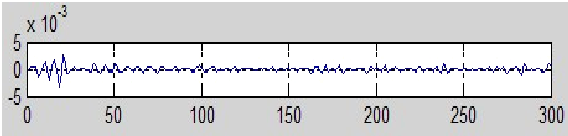

Fig. 19. High frequency information of Db2 on the end side.

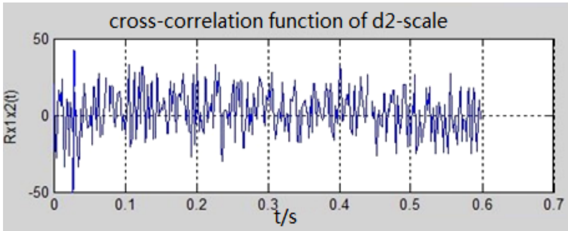

Fig. 20. Cross-correlation function of Db2.

F. In the 1st layer, the high frequency information of signals on the both end are shown in Fig. 21 and Fig. 22. The result of cross-correlation analysis for the signals in this scale is shown in Fig. 23. We can see the time delay from the results and $\Delta t = 0.1474\text{s}$.

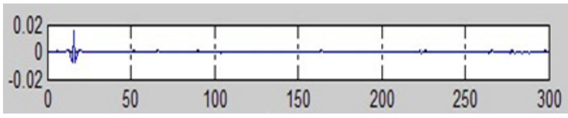

Fig. 21. High frequency information of Db1 on the start side.

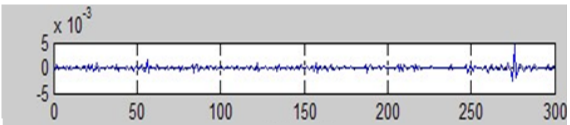

Fig. 22. High frequency information of Db1 on the end side.

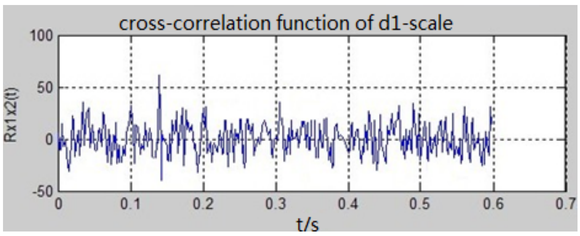

Fig. 23. Cross-correlation function of Db1.

Cross-correlation analysis is done to the high-frequency coefficients which come from wavelet decomposition in d1 to d6 scale, and weighting analysis of the results should be done, and the fusion result is shown in Table 3.

Table 3. Results of fusion algorithm.

Scale Number	Sampling Number	Time Difference Δt (s)
d 1	147	0.147
d 2	22	0.022
d 3	118	0.118
d 4	132	0.132
d 5	113	0.113
d 6	167	0.167
Weight Computation	117	0.117

According to the improved multi-scale cross-correlation analysis of wavelet decomposition, distance between leakage point and the start side sensor is x:

$$x = \frac{L + v * \Delta t}{2} = \frac{50 - 1000 * 0.117}{2} = 33.5\text{m}, \quad (36)$$

And positioning error is:

$$\frac{33.5 - 3}{50} \times 100\% = 0.61\%, \quad (37)$$

The positioning error of multi-scale correlation analysis of wavelet is greatly reduced. It says that improved multi-scale correlation analysis algorithm has certain improvement in the detection and location of leakage signal and the positioning is more precise. More information about the leak can be got according to multi-scale correlation analysis of wavelet.

As seen from the data in Table 4, compared with wavelet decomposition algorithm and multi-scale cross-correlation analysis, multi-scale cross-correlation analysis that based on wavelet decomposition improves the SNR of reconstructed signal and a smaller mean square error can be gotten.

Table 4. Results of comparing SNR and MSE of three algorithms.

Performance index	SNR	MSE
Wavelet decomposition algorithm	24.937	1.200
Multi-scale cross-correlation analysis	25.553	1.251
related fusion of Wavelet multi-scale	28.302	0.096

5. Conclusions

According to the improvement for wavelet decomposition algorithm and the analysis for multi-scale correlation algorithm, we can do cross-correlation analysis to the signal of pipeline leakage on multi-scale. The corresponding sample point of leak mutation can be got according to calculation of weight for singular value point. The experimental results show that Multi-scale correlation analysis algorithm of wavelet decomposition has several advantages as follows: the accuracy of positioning is high; the SNR of signal is high; the MSE of signal is low. So the aim to improve the accuracy of infrasonic signal for leak detection has been finished.

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