A study of characteristics extraction of dynamic pressure signals in pipeline based on EMD

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Abstract

Characteristic selection is a key to accurate signal recognition. Specific to the signal recognition of dynamic pressure waves in pipelines, this article proposes to use EMD method to decompose dynamic pressure signals into a series of IMFs, adopt the correlation theories of signals to determine and eliminate noise, retain valid IMFs from 4th to 8th level and extract kurtosis, energy and statistical characteristics. The experiment analyses and verifies that the energy or statistical characteristics (mean variance, mean standard deviation, mean range and mean quartile range) can effectively represent signals.

Keywords: EMD, kurtosis, energy, statistics, characteristic

1 Introduction

The research of pipeline leakage detection technology started from 1970s. Due to the differences in measuring media, there are mainly two detection methods: direct detection and indirect detection [1].The negative pressure wave method used in indirect detection method only requires pressure transmitters on both sides of the pipeline to detect the real-time changes in pressure. It is widely used in China as it does not need a mathematic model, is convenient in construction and maintenance, costs relatively low and fits China's pipe network [2]. When a pipeline leaks, the pressure in the leaking point decreases out of a sudden and surrounding fluid will flow towards it. Such a phenomenon is called the wave fluctuations of negative pressure wave which spreads to both sides of the pipeline when leakage takes place. It has characteristics of long distance of spread, instant responsiveness and reliable signals. Actual pressure signals, including normal pressure wave, negative pressure wave and other effective signals and noises generated by environment, are collected by pressure transmitter. They are non-linear, non-stationary, vibrating signals with noise and can be analysed and recognized after de-noising.

Empirical Mode Decomposition (EMD), a non-linear, non-stationary signal processing method, was proposed in 1998 by Dr. Nomen E, Huang (Huang E) and his colleagues in Goddard Space Flight Centre in National Aeronautics and Space Administration (NASA) [3]. It has been applied in damage detection, biotechnology, filtration, de-noising and other areas. EMD aims to decompose adaptively a time series signal, according to its own time measurement, into an Intrinsic Mode Function (IMF) with both orthogonally and completeness [4]. These IMFs are decomposed according to the frequency sequence from high to low. Analysis of all variants is useful for measuring the signals' characteristics more effectively and accurately. Such an assembly of IMFs according to the frequency equals to the high-pass, low-pass and band-pass filtration of all signals. Among common filtration methods, Fourier transform primary function is a trigonometric function , suitable for time-frequency analysis of stationary signals. The short-time Fourier transform (STFT), Gabor Transform, wavelet analysis and other methods were proposed to analyse non-stationary signals. However, their primary functions are fixed without adaptively, and the de-noising effects of wavelet analysis rely on the artificial selection of wavelet basis and decomposition layers [5]. Therefore, EMD method with adaptively is more suitable for the processing and analysis of the instant pressure signals in non-linear and non-stationary pipelines.

This article adopts EMD method to decompose the pressure signals in petroleum pipeline into a series of IMFs and measure the signal fluctuations of the IMFs under different frequencies. It analyses the validity of IMFs according to autocorrelation and cross-correlation with original signals and composes all valid IMFs to constitute de-noising signals. It proposes to pick up kurtosis [6], energy and statistical characteristics of the de-noising signals and, through SVM method, compares the effectiveness of these characteristics to describe pressure signals.

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2 De-noising of dynamic pressure signals based on EMD

The pipeline pressures signals that dynamic pressure transmitters collect are non-linear, non-stationary, noise-including, vibrating signals. With EMD, signals can be decomposed into a series of IMFs according to the frequency from high to low. Choose IMFs within valid frequencies according to signals characteristics to compose new signals. Such a process equals to the filtration of original signals.

2.1 DECOMPOSITION OF DYNAMIC PRESSURE SIGNALS BASED ON EMD

The EMD method assumes that [3] all signals composed of a series of different IMFs. Each IMF can be linear or non-linear, stationary or non-stationary. Each IMF should satisfy two requirements: the number of extreme points and the number of zero points of the curves equal or have a maximum difference of 1; on any point in the curve, the average of the maximum extreme point and minimum extreme point of the envelop equals zero, namely that the envelop is symmetrical on the time axis. EMD method decomposes signals according to the time characteristics of the data series. There is no need to present a primary function. It is a data-driven signal analysis method with adaptively, suitable to process frequency-transient signals, non-stationary and non-linear signals.

When the negative pressure wave method detects pipeline leakages, the pressure wave signals that the pressure transmitters at both sides of the pipeline collect are non-stationary. The EMD method, when decomposing signals, can analyse IMFs with different frequencies and different vibrating modes, therefore requiring wave information within the signals. After decomposition, original signal $x(t)$ is decomposed into a combination of finite IMFs and one residual $r(t)$.

$$x(t) = \sum_{i=1}^{n} imf_i(t) + r(t) . \quad (1)$$

Each IMFs is decomposed according to the frequency from high to low and represents the fluctuations of signals under different frequencies. The residual $r(t)$ represents the tendency of the signals.

2.2 SIGNAL ANALYSIS AND DE-NOISING BASED ON EMD

Recently, EMD method has been used in pipeline leakage detection technology to reduce noise interference and to analyse valid signals. As EMD uses cubic spline interpolation data structure to compose the upper and lower envelops of IMFs and due to the requirement of symmetry on the time axis during the decomposition, there exist pseudo-IMFs among all the IMFs decomposed that will interfere the signal analysis. The 6th and 7th articles cited uses the former 6 and former 4 IMFs respectively to re-compose signals, reduce low-frequency signals and residual signals and maintain high-frequency IMFs. The 8th article calculated the correlation of all IMFs with original signals, and used three IMFs with highest correlation coefficients to de-compose negative pressure wave signals. The 5th article selected IMFs from 5th to 8th levels and residual signals to compose valid signals. It used the cross-correlation and auto-correlation of signals to measure the valid IMFs within all the actual signals in the test oil fields.

The 9th article proposed the detection of noise by analysing the cross-correlation and auto-correlation of IMFs and original signals. The correlation coefficient of white noise and original signals is zero. If the correlation coefficient $R_{x\,imf_i}(\tau)$ of a certain $imf_i(t)$ and original signal $x(t)$ is smaller, then such a function can be noise:

$$R_{x\,imf_i}(\tau) = E\left[x(t)imf_i(t+\tau)\right], \quad (2)$$

where if the correlation coefficient $R_{\dddot{imf}_i(\tau)}$ of suspected noise $\dddot{imf}_i(t)$ is small at each point except the maximum at point zero, such a function can be determined to be noise. Therefore, it is verified that the correlation coefficient of white noise is zero at each point except the maximum at point zero.

$$R_{\dddot{imf}_i(\tau)} = E\left[\dddot{imf}_i(t)\dddot{imf}_i(t+\tau)\right]. \quad (3)$$

Due to the existence of decomposition error of regional wave, last few functions are always pseudo-functions. As pseudo-functions have low correlation with original signals, they can be excluded without influencing the analysis result.

2.3 CORRELATION ANALYSIS AND DE-NOISING OF FIELD-MEASURED SIGNALS

The characteristic of field-measured signals is that the intrinsic signals are overwhelmed by noise and that signals tend to perform like high-frequency noise. Therefore, correlate the decomposed IMFs with original signals. Those IMFs with high correlation coefficients represent noise and those with the lowest are usually pseudo-functions. If the correlation coefficient $R_{\dddot{imf}_i(\tau)}$ of IMFs is small except the maximum at point zero, it can be determined to be noise.

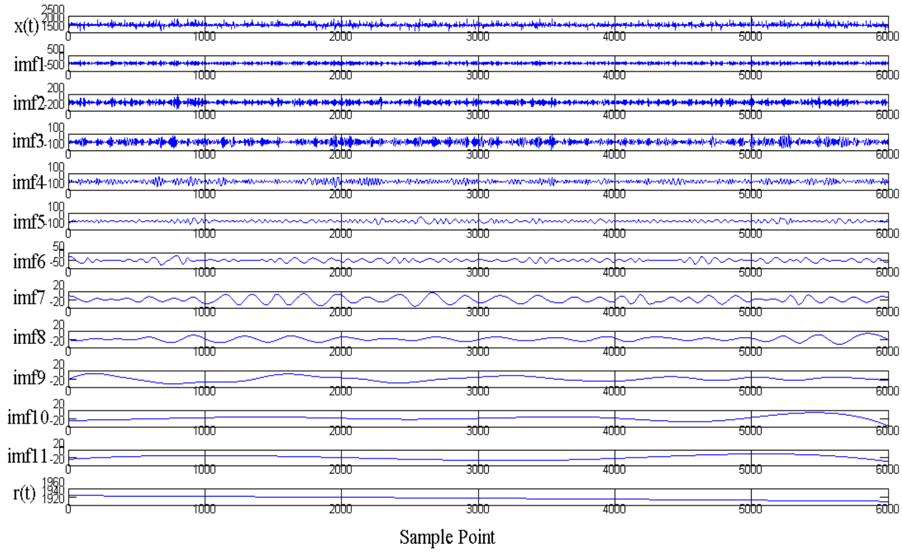

FIGURE 1 Normal Signals and its IMFs after EMD

Normal signals and its IMFs after EMD are shown in Figure 1, where $x(t)$ is the collected signal. IMF 1 to IMF 11 are IMFs after EMD at various levels. They are decomposed according to the frequency from high to low and the decomposed form is unique. Each IMF represents the changes of signal amplitude under a certain frequency with the changes of sampling time. $r(t)$ is the residual which represents the tendency of signals. The calculation of the cross-correlation coefficients of each IMF and original signals $x(t)$ is shown in Table 1. In the table, those IMFs with high correlation coefficients at the upper levels are noise; those with low correlation coefficients at the lower levels are pseudo-functions. Calculate and draw an auto-correlation graph of IMFs, as shown in Figure 2. It can be seen that, the IMFs decomposed earlier have more obvious characteristics of white noise.

TABLE 1 Cross-Correlation Coefficients of Normal Signals and its IMFs

$R_{0,1}$	$R_{0,2}$	$R_{0,3}$	$R_{0,4}$	$R_{0,5}$	$R_{0,6}$	$R_{0,7}$	$R_{0,8}$	$R_{0,9}$	$R_{0,10}$	$R_{0,11}$	$R_{0,12}$
0.6272	0.4285	0.2942	0.2072	0.1407	0.1106	0.0761	0.0448	0.0688	0.0759	0.0786	0.0165

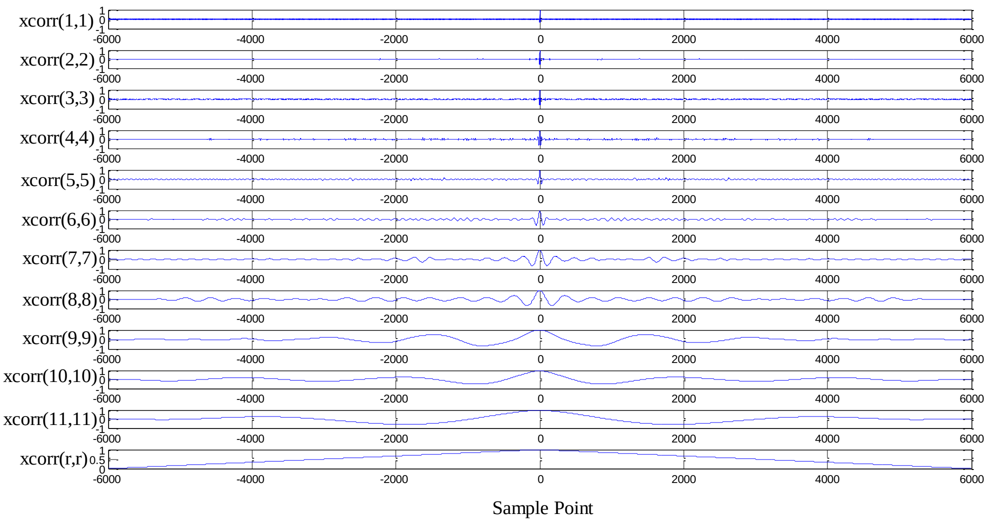

FIGURE 2 The Correlation of Normal Signals and its IMFs

The leakage signals and its IMFs after EMD are shown as Figure 3. The leakage signals are also decomposed into IMFs of 11 layers and one residual $r(t)$. The cross-correlation coefficients of each IMF and the original signal $x(t)$ are shown in Table 2. The auto-correlation of each IMF is shown in Figure 4.

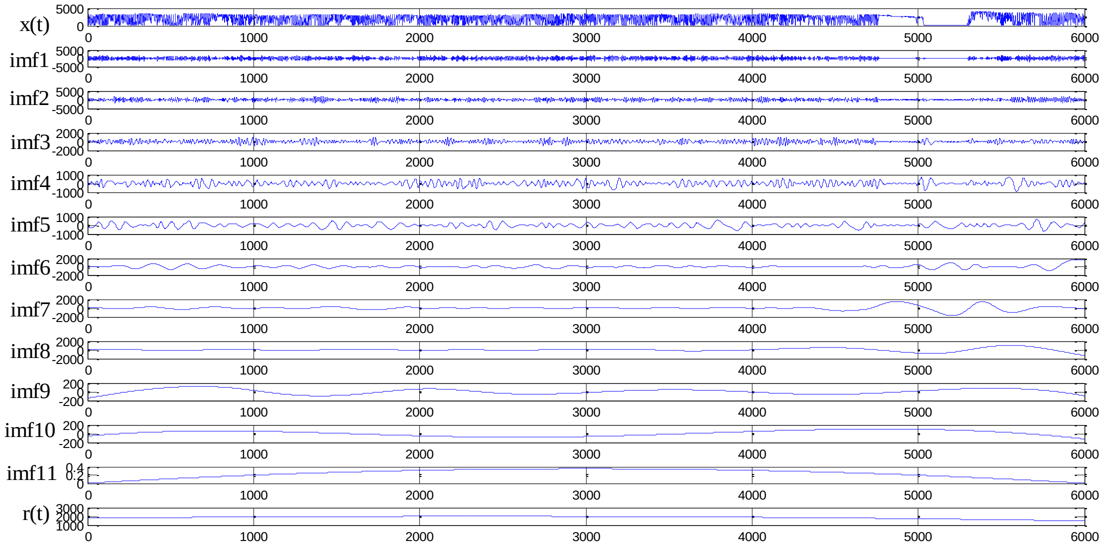

FIGURE 3 Leakage Signal and its IMFs after EMD

TABLE 2 The Cross-Correlation Coefficients of Leakage Signals and its IMFs

$R_{0,1}$	$R_{0,2}$	$R_{0,3}$	$R_{0,4}$	$R_{0,5}$	$R_{0,6}$	$R_{0,7}$	$R_{0,8}$	$R_{0,9}$	$R_{0,10}$	$R_{0,11}$	$R_{0,12}$
0.5793	0.4870	0.2226	0.1982	0.2121	0.1829	0.3549	0.1978	0.0141	-0.0024	0.0110	0.0223

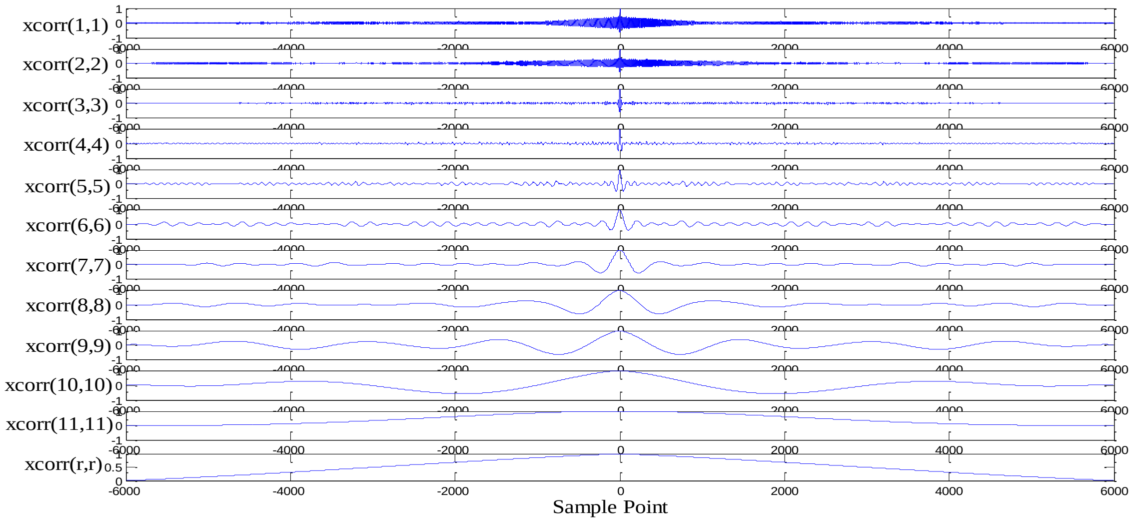

FIGURE 4 Cross-correlation of Leakage Signals and IMFs

To analyse comprehensively, eliminate the IMFs with high frequencies and white noise characteristics and pseudo-IMFs with low frequencies and low amplitude, retain IMFs from 4th to 8th level and reconstruct signals. The signals retain the characteristics of original signals after de-noising and adopting transform the average value of function to nought, as shown in Figures 5 and 6.

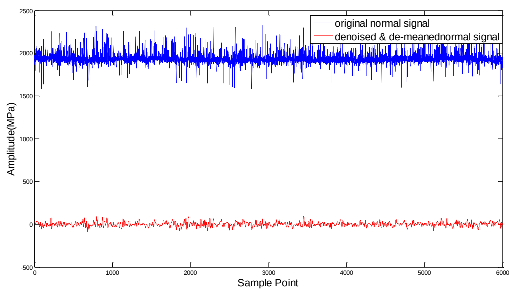

FIGURE 5 Normal Signal

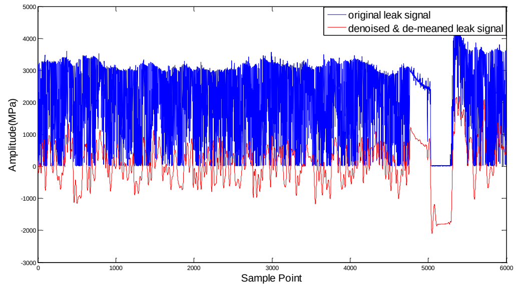

FIGURE 6 Leakage Signal

3 Three characteristic extraction methods

After de-noising and de-meaning, the turbulence characteristic of dynamic pressure wave signals is very obvious, with noticeable characteristics of a one-dimensional time series. The signal characteristics of normal signals and leakage signals are remarkably different. The following analysis selects signal characteristics from kurtosis, energy and statistics, and compares the effective characteristic description method of signals.

3.1 KURTOSIS CHARACTERISTIC

Kurtosis is a non-dimensional parameter to describe the peak of waves, often used in fault diagnosis. The 6th and 7th articles used the normalized kurtosis of IMFs as the main characteristic parameter of dynamic pressure signals. This article uses the normalized kurtosis of the IMFs from 4th to 8th levels of an oil field measured signals as the signal descriptive characteristic.

The Equation (4) is for kurtosis calculation. μ_{imf_i} and σ_{imf_i} are the mean value and the standard deviation of the IMF on i level. $E(t)$ calculates the expected value of the variant, $i \in [4,8]$.

$$K_i = \frac{E\left(imf_i - \mu_{imf_i}\right)^4}{\sigma_{imf_i}{}^4}. \qquad (4)$$

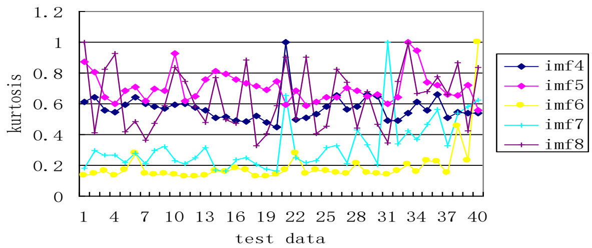

FIGURE 7 Kurtosis of IMF of Test Data

Figure 7 illustrates the zoomed kurtosis (between 0 and 1) of IMFs from 4th to 8th level from an EMD of 40 pairs of test data. The previous 30 pairs are normal data while the latter 10 are leakage data.

3.2 ENERGY CHARACTERISTIC

The 2nd article pointed out that Hilbert-Huang transform could provide accurately the conjoint analysis of signal energy with changes in frequency and time. Use the normalized energy of IMFs from 4th to 8th level as signal descriptive signal. The signal characteristics in Graph 7 are shown in Figure 8.

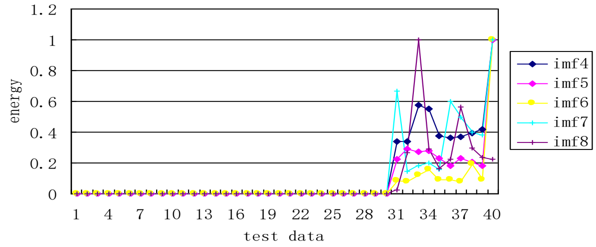

FIGURE 8 Energy Characteristics of IMF of Test Data

3.3 STATISTICAL CHARACTERISTIC

Statistical characteristic is an efficient method to describe time series data with even intervals. Use the mean value of statistical characteristics of IMFs from 4th to 8th level to describe the signals. The signal characteristics (Figure 7) are shown in Figure 9.

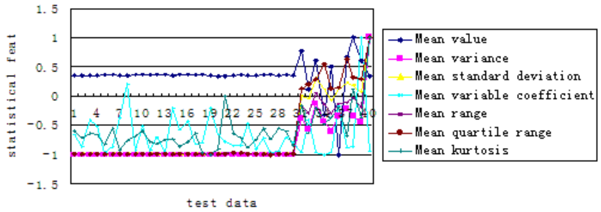

FIGURE 9 Average Statistical Characteristics of IMFs in Test Data

3.4 CHARACTERISTIC EXTRACTION

The 10th article proposed 3 standards to select leakage signals:

1) given that data length stays the same, wherever the leakage signals appears in this data, its characteristic values are basically the same;

2) for the leakage signals that take place at different time and under different working conditions, the characteristic values collected at a same detection spot are basically the same;

3) the maximum characteristic values of normal signals are smaller than the characteristic values of leakage signals or at least most characteristic values satisfy this standard. Therefore, in characteristic extraction, the characteristic values of normal signals and of leakage signals have their respective data range and the differences in values are large and they stay stable in their own range. According to these standards and the result of data analysis, this article chooses two characteristic descriptive pressure wave signals, namely the energy characteristics and the average statistical characteristics of IMFs from 4th to 8th level:

mean variance, mean standard deviation, mean range and mean quartile range.

4 Study of Signal Recognition

Whether the selected signal characteristics can effectively represent the actual signals needs to be verified by field measurement. This article uses SVM to select characteristics and to carry out leakage identification forecast for the leakage signals after EMD and de-noising.

4.1 SIGNAL RECOGNITION EXPERIMENT BASED ON SVM

This article uses C-SVM method (suitable for small samples) with LibSVM tool cabinet. It chooses RBF kernel functions to build models for the 2 characteristics of 40 pairs of field-measured data and optimizes with grid method. Then it applies the model to categorize the 10 pairs of test data with 100% categorization accuracy. It is shown in Table 3.

TABLE 3 Recognition Result of Different Characteristics

Selected Characteristic	c	g	Categorization Accuracy of Training Set	Categorization Accuracy of Testing Set
Energy Characteristic	0.1895	3.0314	100%	100%
Statistical Characteristic	0.1895	1.7411	100%	100%

4.2 LOCATING EXPERIMENT OF SIGNAL LEAKAGE WITH EMD AND DE-NOISING

The experimental pipeline has a length of $L(km)$. If a leakage occurs $X(km)$ from the upper stream, the negative pressure wave spreads to the upper and the lower stream with a speed of $v(m/s)$. The time difference to reach the upper and the lower stream is Δt. So the pipeline leakage locating formula is as below:

$$X = \frac{1}{2}\left(L - v \times \Delta t\right), \tag{5}$$

where the method of maximum auto-correlation of signals in the upper and lower streams can get Δt. The pipeline is 4.2 km with dynamic pressure transmitters at both sides of the pipeline to collect instant pressure signals. The interval of sampling signals is 20 ms with sampling frequency of 50Hz. Each sampling takes 1 minute. Total sampling points are 3000. To ensure the completeness of the signals, the experiment combines the previous one-minute data with the present one to get an observation signal. So each signal is 2 minutes long and in total there are 6000 sampling points. The pressure wave spreads in the petroleum medium at a speed of 456m/s. Then, carry out correlation analysis of both pressure signals gained from the upper and lower streams of the pipeline and the EMD decomposed and re-composed signals to gain different Δt. Then, use the Equation (5) to calculate the position of leakage. The result is shown in Table 4. The positioning by EMD and de-noising signals is more accurate.

TABLE 4 Leakage Positioning Result

Experiment No.	Actual Leaking Point (km)	Original Signals			EMD and De-noising Signals		
		Δt (ms)	*Positioning (km)*	*Positioning Error (km)*	*Δt (ms)*	*Positioning (km)*	*Positioning Error (km)*
1	2	10	2.0977	0.0977	482	1.9901	0.0099
2	2	98	2.0777	0.0777	474	1.9919	0.0081
3	1	108	2.0754	1.0754	4226	1.1365	0.1365
4	1	8	2.0982	1.0982	1476	1.7635	0.7635
5	1	6	2.0986	1.0986	1490	1.7603	0.7603

5 Conclusions

This article is based on research data from an oil field measured dynamic pressure signals and comes to the following conclusions:

1) EMD method is applicable to the de-noising of dynamic pressure signals in petroleum pipelines.

2) The field-measured data of a pipeline can re-compose signals from 4^{th} to 8^{th} level.

3) EMD and de-noising signals perform better to position the leakage than original signals.

4) The energy characteristics of IMFs from 4^{th} to 8^{th} level can effectively represent signals;

5) The mean statistical characteristics, including mean variance, mean standard deviation, mean range and mean quartile range can effectively represent signals.

6) C-SVM method can effectively recognize dynamic pressure signals.

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