Measurement 124 (2018) 163–172

Contents lists available at ScienceDirect

Measurement

journal homepage: www.elsevier.com/locate/measurement

Natural-gas pipeline leak location using variational mode decomposition analysis and cross-time–frequency spectrum

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ARTICLE INFO

Keywords:
Leak location
Variational mode decomposition
Cross-time–frequency spectrum
Time delay
Dispersive curve

ABSTRACT

A novel method based on variational mode decomposition (VMD) and cross-time–frequency spectrum (CTFS) is proposed for leak location in natural-gas pipelines. Leakage signals are decomposed into mode components by VMD, and an adaptive selection method using mutual information is proposed to process these mode components and obtain the sensitive components closely related to the leak. CTFS is applied to analyze the time–-frequency distribution of sensitive mode components. The delay and the corresponding frequency information are extracted when CTFS reaches the maximum. The corresponding frequency is used to calculate the group velocity of wave speed, in combination with the dispersive curve. Finally, the time-delay information and wave speed can be used to determine leakage source. The proposed scheme has been experimentally validated; the results demonstrate that the average relative location errors are reduced to one-third when compared with the CTFS location method based on empirical mode decomposition (EMD).

1. Introduction

Recently, as the natural-gas demand increases with each passing day, gas pipelines have undergone dramatic developments [1,2]. However, leaks occur frequently for reasons such as pipeline corrosion and weld defects; this poses an enormous hidden threat to the safe operation of the pipeline. Hence, it's necessary to conduct locating study of pipeline leakage source and guarantee safe operation of natural-gas pipeline systems [3–5]. The current methodologies primarily require special sensing devices to detect and locate pipeline leaks, such as cable sensor, optical fiber, and acoustic monitoring [6–8]. However, these methods are complexity of installation, and very expensive.

When a pipeline suffers a leak, gas–solid coupling occurs between the gas that escapes rapidly and the leakage hole in the wall; this generates stress waves that will spread along the pipeline to either side of the leakage hole [9,10]. He Cunfu et al. [10] regarded the stress wave as a kind of acoustic-emission signal and applied it in the leakage-location procedure; this process obtained a good location result. Therefore, this study uses this acoustic-emission technique to locate the source of leak in a natural-gas pipeline. The traditional acoustic-emission location method mainly uses cross-correlation to calculate the delays in the leakage signals, which assumes the wave speed to be known and to be constant [11–13]. However, a dispersion phenomenon occurs when the leakage signal is transmitted along the pipe wall. The wave speed varies with the frequency and the assumption is not supported, resulting in missing the detection and location of a gas leak [4,14–17]. Hence, the location study of dispersive signals is of great significance.

Because the leakage signals generated by a pipeline leak are non-stationary, a non-stationary signal processing method must be employed to obtain information from the leak [18]. Conventional signal analysis methods such as the windowed Fourier transform, which requires that the signals meet stationary and linear assumptions [19]. The wavelet analysis method has advantageous local features in the time and frequency domains and is thus more suitable for the analysis of acoustic emission signal characteristics than windowed Fourier transform [8]. As wavelet analysis is essentially an adjustable window Fourier transformation, energy leakage occurs inevitably owing to the limited length of the wavelet base function. On the other hand, once the wavelet base function and decomposition scales have been determined, the results of a wavelet transform will be solely functions of the sampling frequency [20,21]. The EMD, which is a classical non-stationary signal processing method [19], can self-adaptively decompose a complicated multi-component signal into the sum of several intrinsic mode functions (IMFs) components and use this IMF to calculate the instantaneous frequency and amplitude [22,23]. As the EMD process is completely based on the characteristics of the signal, there is no requirement for manual selection of the basis function. Therefore, it has

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https://doi.org/10.1016/j.measurement.2018.04.030
Received 15 June 2016; Received in revised form 31 March 2018; Accepted 9 April 2018
Available online 11 April 2018
0263-2241/

been extensively applied in fields like mechanical failure diagnosis and EEG processing; however, this method still has some defects such as the mode-mixing effect, end effect, etc. [24–26]. VMD is a new non-stationary signal processing method proposed in 2014, its decomposition process determines the center frequencies and bandwidths of the mode components after decomposition through an iterative seek for an optimal solution to the variational model, by which it can self-adaptively decompose non-stationary signals [27,28]. Compared to the recursive "screening" mode of the EMD, VMD can non-recursively decompose a multi-component signals into a number of components and controls the decomposition convergence conditions reasonably [29]. Hence, the decomposition process can effectively eliminate the mode-mixing phenomenon with good noise immunity.

Based on the above analysis, this paper proposes a leakage-source location method for natural-gas pipelines based on VMD and CTFS. The VMD method is used to analyse the leakage signal and obtain accurate mode components. A mutual-information–based adaptive selection method is proposed to select the sensitive mode components of the leakage signals. CTFS analysis of the sensitive mode components, of the leakage signals collected by different sensors, can obtain the delay and the corresponding frequency information of the leakage signals; the corresponding frequency information can be used to acquire the frequency-dependent wave speed. Finally, the source of the leak can be located using the frequency-dependent wave speed and delay, according to the proposed method.

The remainder of this paper is organized as follows. Section 2 discusses the VMD method. Section 3 is dedicated to a description of the proposed adaptive selection algorithm based on mutual information, and a simulation is generated to illustrate the method. In Section 4, the location method based on VMD and CTFS is presented. The proposed leak-location scheme is experimentally validated and compared with the location method based on CTFS and EMD in Section 5, and the conclusions of this paper are given in Section 6.

2. Variational mode decomposition

Variational mode decomposition is a new self-adaptive signal processing method, which was first proposed by Dragomiretskiy in 2014. This method achieves self-adaptive decomposition of the signal through the construction and solution of variational problems [27–29]. Any signal $f(t)$ can be written in the following form:

$$f(\mathrm{t}) = \sum_k u_k(\mathrm{t}) \tag{1}$$

In Eq. (1), $u_k(\mathrm{t})$ is the component after decomposition. $u_k(\mathrm{t})$ is defined as a frequency-modulation–amplitude-modulation (AM–FM) signal, and its mathematical expression is as follows:

$$u_k(\mathrm{t}) = \mathrm{A}_k(\mathrm{t})\cos(\phi_k(\mathrm{t})) \tag{2}$$

In Eq. (2), $\mathrm{A}_k(\mathrm{t})$ is the instantaneous amplitude and $\omega_k(\mathrm{t})$ is the instantaneous frequency; $\omega_k(\mathrm{t})$ is given by $\omega_k(\mathrm{t}) = \phi_k'(\mathrm{t}) = \frac{d\phi_k(\mathrm{t})}{dt}$.

The VMD algorithm transfers the signal decomposition process into the variational framework. Hence, the decomposition process of the VMD is an optimal-solution processing for a constrained variational process. The mathematical expression of its corresponding constrained variational model is as follows:

$$\min_{\{u_k\},\{\omega_k\}} \left\{ \sum_k \left\| \partial_t \left[\left(\delta(\mathrm{t}) + \frac{j}{\pi t} \right) u_k(\mathrm{t}) \right] e^{-j\omega_k t} \right\|_2^2 \right\} \tag{3}$$

In Eq. (3), $\{u_k\} = \{u_1,...,u_k\}$ represents k components after decomposition and $\{\omega_k\} = \{\omega_1,...,\omega_k\}$ represents the center frequencies of the components after decomposition; $\delta(t)$ is impulse function.

For constrained-variation problems, the augmented Lagrange function is introduced to transform the constrained variation problem into an unconstrained variation problem; the mathematical expression for the augmented Lagrange function is as follows:

$$L(\{u_k\},\{\omega_k\},\lambda) = \alpha \sum_k \left\| \partial_t \left[\left(\delta(\mathrm{t}) + \frac{j}{\pi t} \right) u_k(\mathrm{t}) \right] e^{-j\omega_k t} \right\|_2^2 + \left\| f(\mathrm{t}) - \sum_k u(\mathrm{t}) \right\|_2^2 + \left\langle \lambda(\mathrm{t}), f(\mathrm{t}) - \sum_k u_k(\mathrm{t}) \right\rangle \tag{4}$$

In Eq. (4), α is the penalty parameter and λ is the Lagrange multiplier.

In order to solve the problem of obtaining an optimal solution, the alternate direction method of multipliers (ADMM) is used to calculate the saddle point of the augmented Lagrange function, which is the optimal solution of the constrained-variation equation [30]. The saddle-point problem is solved by the alternate renewal of u_k^{n+1}, ω_k^{n+1}, and λ^{n+1}, i.e., solving the optimal-solution problem of the variational problem. The mathematical expressions of u_k^{n+1} and ω_k^{n+1} are as follows:

$$u_k^{n+1} = \underset{u_k \in X}{\operatorname{argmin}} \left\{ \alpha \left\| \partial_t \left[\left(\delta(\mathrm{t}) + \frac{j}{\pi t} \right) * \mathrm{u}_k(\mathrm{t}) \right] \mathrm{e}^{-j\omega_k t} \right\|_2^2 + \left\| f(\mathrm{t}) - \sum_i u_i(\mathrm{t}) + \frac{\lambda(\mathrm{t})}{2} \right\|_2^2 \right\} \tag{5}$$

$$\omega_k^{n+1} = \underset{\omega_k}{\operatorname{argmin}} \left\{ \left\| \partial_t \left[\left(\delta(\mathrm{t}) + \frac{j}{\pi t} \right) * \mathrm{u}_k(t) \right] \mathrm{e}^{-i\omega_k t} \right\|_2^2 \right\} \tag{6}$$

In Eqs. (5) and (6), ω_k is equal to ω_k^{n+1}, and $\sum_i u_i(\mathrm{t})$ is equal to $\sum_{i \neq k} u_i(\mathrm{t})^{n+1}$.

The Parseval/Plancherel Fourier isometric transformation is used to transform Eqs. (5) and (6) into the frequency domain, thus updating the frequency domain and center frequencies of the modes. Their mathematical expressions are as follows:

$$\hat{u}_k^{n+1}(\omega) = \frac{\hat{f}(\omega) - \sum_{i \neq k} \hat{u}_i(\omega) + \frac{\hat{\lambda}(\omega)}{2}}{1 + 2\alpha(\omega - \omega_k)^2} \tag{7}$$

$$\omega_k^{n+1} = \frac{\int_0^\infty \omega |\hat{u}_k(\omega)|^2 d\omega}{\int_0^\infty |\hat{u}_k(\omega)|^2 d\omega} \tag{8}$$

In Eq. (7), $\hat{u}_k^{n+1}(\omega)$ is equal to the Wiener filter of $\hat{f}(\omega) - \sum_{i \neq k} \hat{u}_i(\omega)$. The gravity center of the current modal function power spectrum in Eq. (8) is ω_k^{n+1}, and the real part of $\{\hat{u}_k(\omega)\}$ conducting Fourier inversion is $\{u_k(t)\}$.

The VMD algorithm continuously updates the modes in the frequency domain, and finally transforms them into the time domain through the Fourier inversion. The specific algorithm is as follows:

(1) Initialize $\{\hat{u}_k^1\}$, $\{\omega_k^1\}$, $\hat{\lambda}^1$, and $n = 0$.
(2) $n = n + 1$ Executes the whole loop.
(3) Execute innermost loop, $k = 1{:}\ K$, u_k and ω_k are renewed according to $\hat{u}_k^{n+1}$ and ω_k^{n+1}.

$$\{\hat{u}_k^{n+1}\} = \frac{\hat{f}(\omega) - \sum_{i<k} \hat{u}_i^{n+1}(\omega) - \sum_{i>k} \hat{u}_i^{n}(\omega) + (\hat{\lambda}^n(\omega)/2)}{1 + 2\alpha(\omega - \omega_k^n)^2} \tag{9}$$

$$\omega_k^{n+1} = \frac{\int_0^\infty \omega |\hat{u}_k^{n+1}(\omega)|^2 d\omega}{\int_0^\infty |\hat{u}_k^{n+1}(\omega)|^2 d\omega} \tag{10}$$

(4) Renew λ according to $\hat{\lambda}^{n+1}(\omega)$ for $\omega \geqslant 0$.

$$\hat{\lambda}^{n+1}(\omega) = \hat{\lambda}^n(\omega) + \tau[\hat{f}(\omega) - sum_k \hat{u}_k^{n+1}(\omega)] \tag{11}$$