Study on the Algorithm of Vibration Source Identification Based on the Optical Fiber Vibration Pre-Warning System

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Abstract: One of the key technologies for optical fiber vibration pre-warning system (OFVWS) refers to identifying the vibration source accurately from the detected vibration signals. Because of many kinds of vibration sources and complex geological structures, the implement of identifying vibration sources presents some interesting challenges which need to be overcome in order to achieve acceptable performance. This paper mainly conducts on the time domain and frequency domain analysis of the vibration signals detected by the OFVWS and establishes attribute feature models including an energy information entropy model to identify raindrop vibration source and a fundamental frequency model to distinguish the construction machine and train or car passing by. Test results show that the design and selection of the feature model are reasonable, and the rate of identification is good.

Keywords: Optical fiber vibration pre-warning system (OFVWS), vibration source identification, attribute feature model, energy information entropy, fundamental frequency stability

1. Introduction

With the rapid development of pipeline transportation, it is very necessary to monitor and protect some important regions like airport, petroleum pipeline, military base, nuclear plant, prison, and bank. The vibration signals from the important surrounding areas are acquired from the optical fiber vibration pre-warning system (OFVWS). The vibration source type is got by analyzing the feature of the vibration signal. If some harmless vibration sources are detected, the alarm can be made. The exact location of the harm events can be reported, the real-time protection for the crucial areas and surroundings can be made, and the

property loss can be reduced.

Recently, the research on vibration signal processing and vibration source identification mainly contains the blind source separation technology [1–7], a signal processing method extracting source signals without knowing or only knowing a little prior information, which is especially applied to communication reconnaissance areas. This technology is currently only effective for the cycle stationary signal while in reality there are always anti-stationary random signals. Hence, it is the key to conduct on source separation for anti-stationary random signals. The blind identification technology for vibration signals [8–10] has some limitations for the separation of multiple

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source signals. The method and theory, wavelet analysis, and Hilbert-Huang transform [11, 12] are still in the stage of development. The support vector machine [13] has advantages of more real-time and higher accuracy for identification, but it needs further work for multi-cases.

For the above methods, they have a common feature, that is, a large number of samples are needed for data learning and training, hence the computation load is heavy, and there is still a convergence issue in its practical application. The above methods mainly conduct on the classifier and classification method, but the further research for attribute features is needed.

In OFVWS, the sensor cable is typically buried next to an oil or gas pipeline to detect different kinds of vibration signals as shown in Fig. 1.
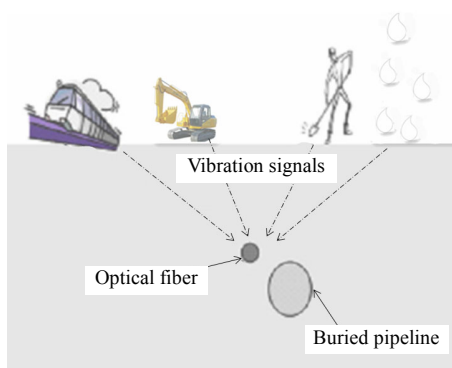

Fig. 1 Cross section of a buried fiber optical intrusion detection system for detection vibration signal.

This paper mainly puts researches on the attribute features of the vibration signals collected by OFVWS, then attribute feature models are established, respectively. The vibration source identification accuracy can be improved through the proposed algorithm in this paper. Test results show that the design and selection of the feature model are reasonable, and the rate of identification is good.

2. Introduction to vibration source identification system

The vibration source identification system belongs to the pattern recognition system. This paper mainly puts researches on the vibration source identification based on OFVWS, as shown in Fig. 2.

A signal acquisition system is used for collecting various vibration signals of security pre-warning areas. The optical fiber cable laid along the pipeline as a distribution sensor is used for the OFVWS to detect various vibration signals. Pre-treatment is a method to obtain data processed by the process of sampling, quantization, and filtering for original vibration signals. A digital signal processing algorithm is used for feature extraction to process data. The database of sources contains various kinds of vibration sources. Feature matching is a method to compare the feature of extracted vibration signals with each template of attributive characters in the database of sources based on the pattern recognition theory, then the similarity distance of waited recognition sources and sources in the database is obtained. Decision is a process to output identification results according to a set of rules.
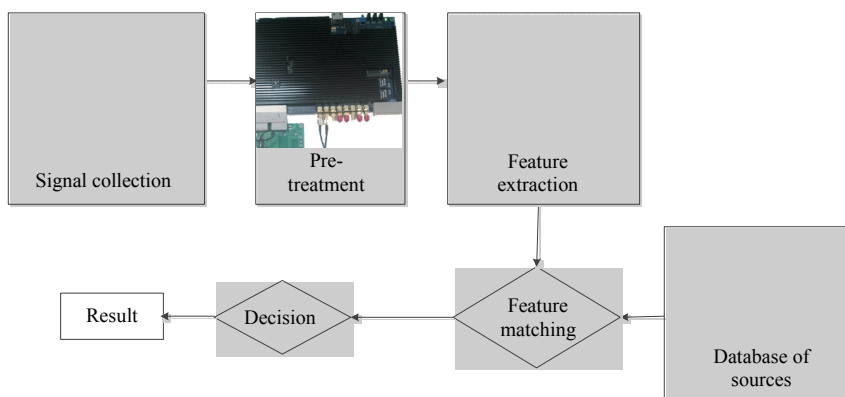

Fig. 2 Structure of vibration source identification system.

This paper focuses on essential features of different vibration sources and conducts on mathematical expression and quantification for the feature of vibration signal. Through the study of known vibration data, a standard library of feature model for various vibration sources can be established.

3. Analysis attribute feature of vibration signal

In this paper, for different vibration signals,

associated characteristics such as amplitude, energy, and probability distribution of energy in the time domain are analyzed. Because the frequency domain analysis of vibration signals like fast Fourier transformation (FFT) and autocorrelation is implemented, essential features of each vibration source can be founded.

3.1 Time domain analysis of vibration signal

Time domain analysis of vibration signal is for analyzing amplitude and energy characteristics.
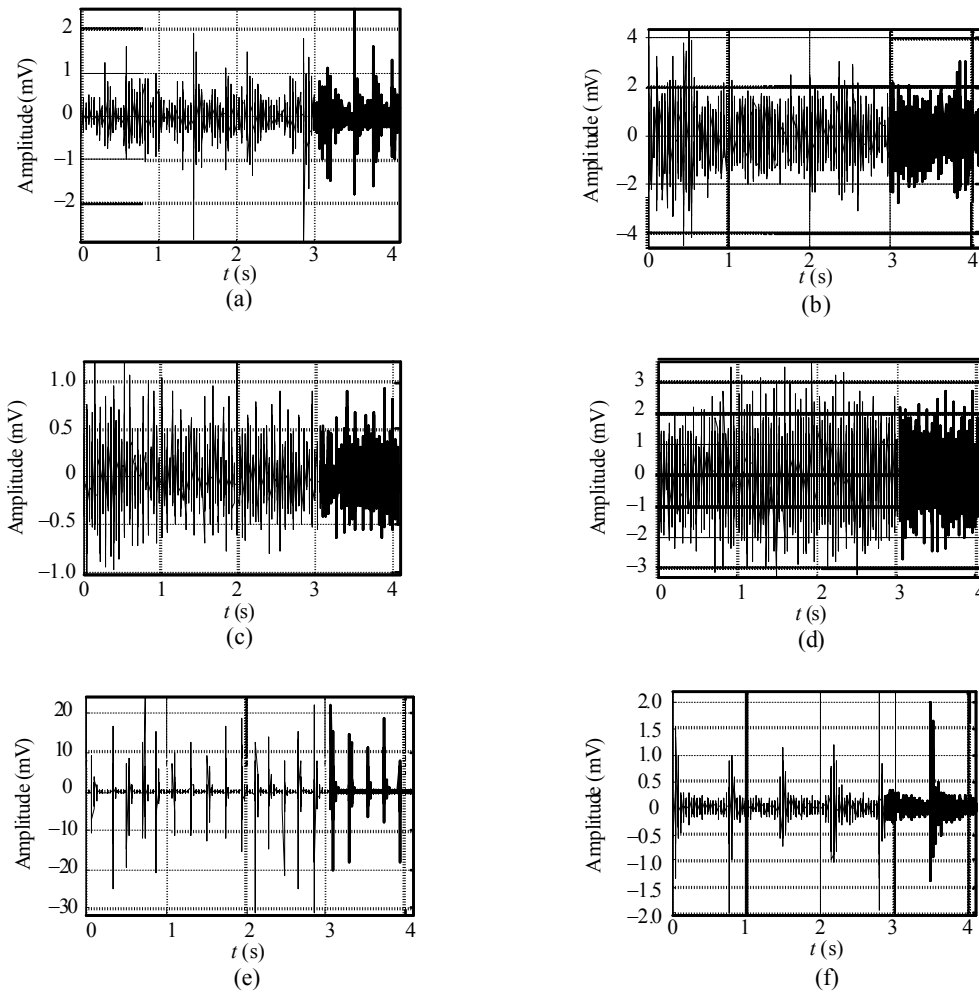
Fig. 3 Waveform analysis of vibration signal amplitude: (a) raindrop, (b) train, (c) broken road machine, (d) large-scale construction machine, (e) knocking optical fiber cable, and (f) knocking well cover.

First, the amplitude and short-time average energy features of vibration signals collected by OFVWS are analyzed. The short-time average energy can be calculated with (1):

$$P_{dB}(n) = 10 \cdot \lg \left(\frac{1}{N} \cdot \sum_{m=n-N+1}^{n} x(m)^2 \right) \qquad (1)$$

where window function is a rectangular window of $1/N$ amplitude and $N=512$, $x(m)$ is vibration data,

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and sampling frequency of photo-detector is 25 kHz. In order to facilitate, the unit of short-time average energy is decibels.

In Figs. 3 (a)–(f), there are amplitude spectra of 100-frame different types vibration signals, respectively. In Figs. 4 (a)–(f), there are short-time average energy waveforms of 100-frame different types vibration signals, respectively.

Then, the average energy statistical characteristics of 1500-frame (about 1 minute) different type vibration signals collected by OFVWS

are analyzed. In Figs. 5 (a)–(f), signal energy scatter plots of 1500 frames vibration signals are shown, respectively. There are statistical probability distribution curves of 1500 frames vibration signals for per frame average energy in Figs. 6 (a)–(f), respectively. The signal energy per frame can be calculated with (2):

$$P_k = 10 \cdot \lg\left(\frac{1}{N} \cdot \sum_{i=1}^{N} x_i^2\right) \tag{2}$$

where P_k is the signal energy in the kth frame, and x_i is the amplitude of ith detected vibration signal.
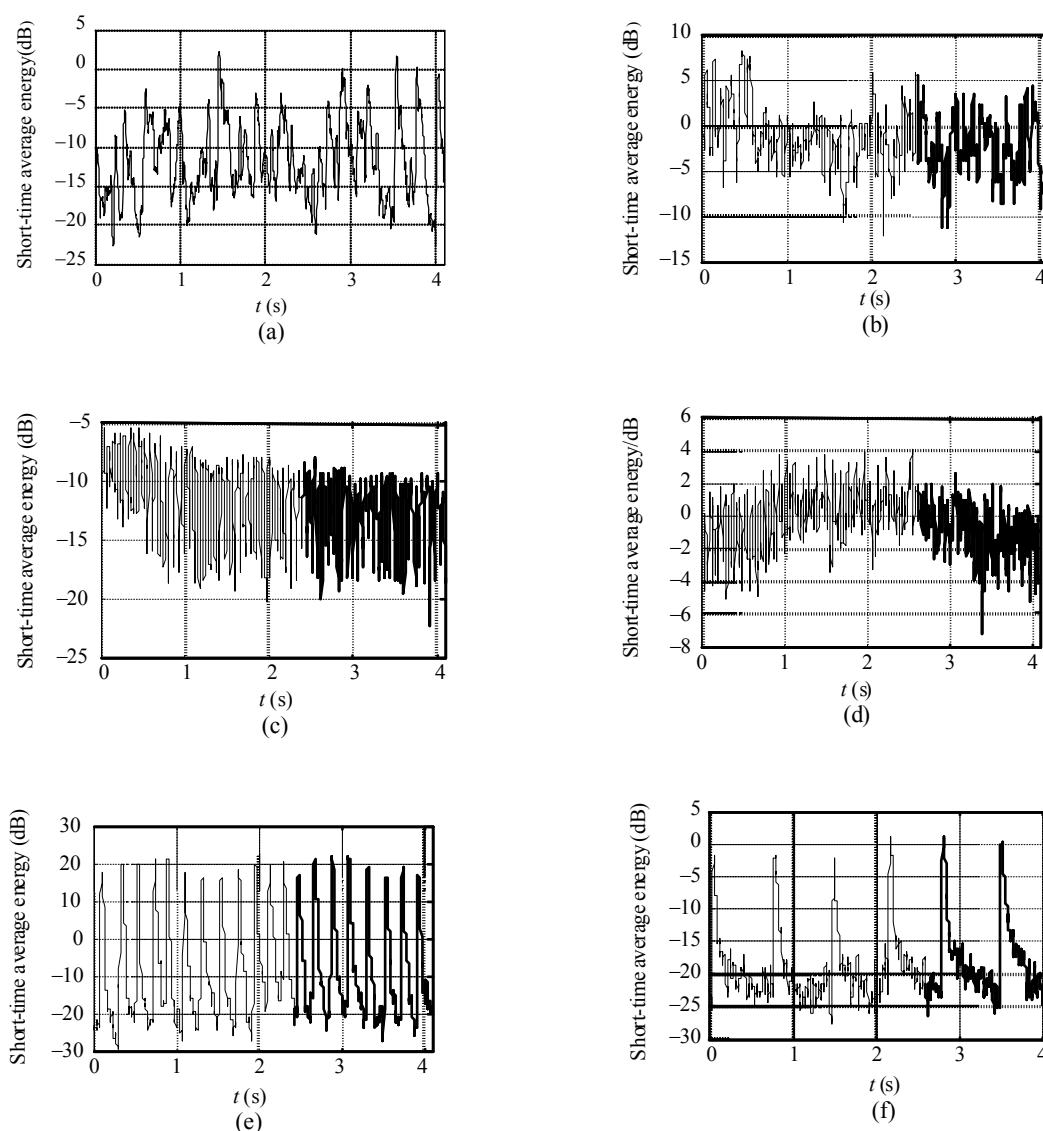

Fig. 4 Waveform analysis of vibration signal short-time average energy: (a) raindrop, (b) train, (c) broken road machine, (d) large-scale construction machine, (e) knocking optical fiber cable, and (f) knocking well cover.

From Figs. 3 and 4, we can observe that:

The signals produced by knocking well cover have obvious features in amplitude: large amplitude and high energy, while the signals produced by the other vibration source have small amplitude which is up to 5 mV. For the noise, the amplitude is about 0.2 mV, the energy is up to 10 dB, and short-time average energy is about −20 dB. The signals produced by human knocking well cover or optical fiber cable have certain periodicity, that is, the knocking occurring at regular and stable intervals. The signals produced by train or car passing by, broken road machines, and large-scale construction machines have high amplitude and energy, that is, these kind signals have a certain duration. It is difficult to distinguish between the raindrop vibration signal and the other noise signals, such as the construction machine.

3.2 Frequency domain analysis of vibration signals

The vibration signals have been analyzed in the frequency domain, by using FFT and a short-time autocorrelation coefficient method. The frequency characteristics of vibration signals can be described.

The short-time autocorrelation coefficient is an item measuring the degree of correlation for one signal in different time, then extracting pitch information of vibration signals, such as correlation of the continuous time signals sequence X_i {$x(i)$, i=1, 2, $\cdots$, n} and the sequence of time shifting k points X_i+k {$x(i)$, i=k+1, k+2, $\cdots$, k+n}. The waveform of short-time autocorrelation coefficient is shown in Fig. 5. A short-time autocorrelation coefficient can be obtained with (3):
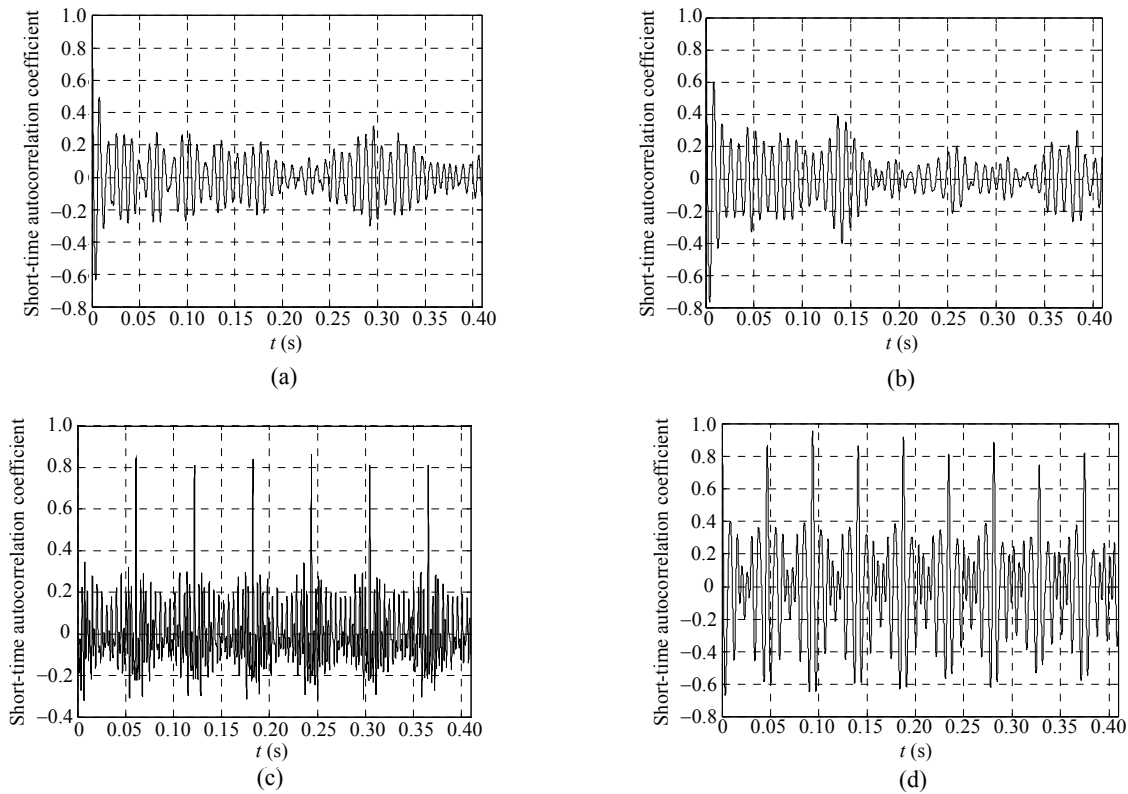

Fig. 5 Waveform of short-time autocorrelation coefficient: (a) raindrop, (b) train, (c) broken road machine, and (d) large-scale construction machine.

$$\rho(k) = \frac{E\left[(X_i - \mu_i)(X_{i+k} - \mu_{i+k})\right]}{\sqrt{D(X_i)}\sqrt{D(X_{i+k})}} \quad (3)$$

$$D(X_i) = \frac{1}{n}\sum_{i=1}^{n}[x_i - \mu_i]^2 \quad (4)$$

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where $\mu_i = \dfrac{1}{n}\sum\limits_{i=1}^{n} X_i$, $\mu_{i+k} = \dfrac{1}{n+k}\sum\limits_{i=1}^{n+k} X_{i+k}$, and $D(X_i)$ is the variance of signal sequence X_i.

From Fig. 5, the short-time autocorrelation coefficient of signals produced by a broken road machine or a large-scale construction machine will have one peak at regular intervals, which can present the fundamental frequency of those two signals, meanwhile, the other signals don't have this feature.

4. Strategy for identifying vibration signals

From the above analysis, a strategy in this paper by using four models is developed to identify these

vibration signals detected by OFVWS, as shown in Fig. 6.

In this identification strategy, vibration signals detected by OFVWS are processed by using four models:

(1) Energy information entropy model

The energy information entropy model is used to check if the detected vibration signals have three typical features of raindrop or not. These three features are the uniform signal energy, the stable energy probability distribution, and the vibration existing stable for a long time, respectively. If the detected vibration signals have these features, they will be the raindrop signals.
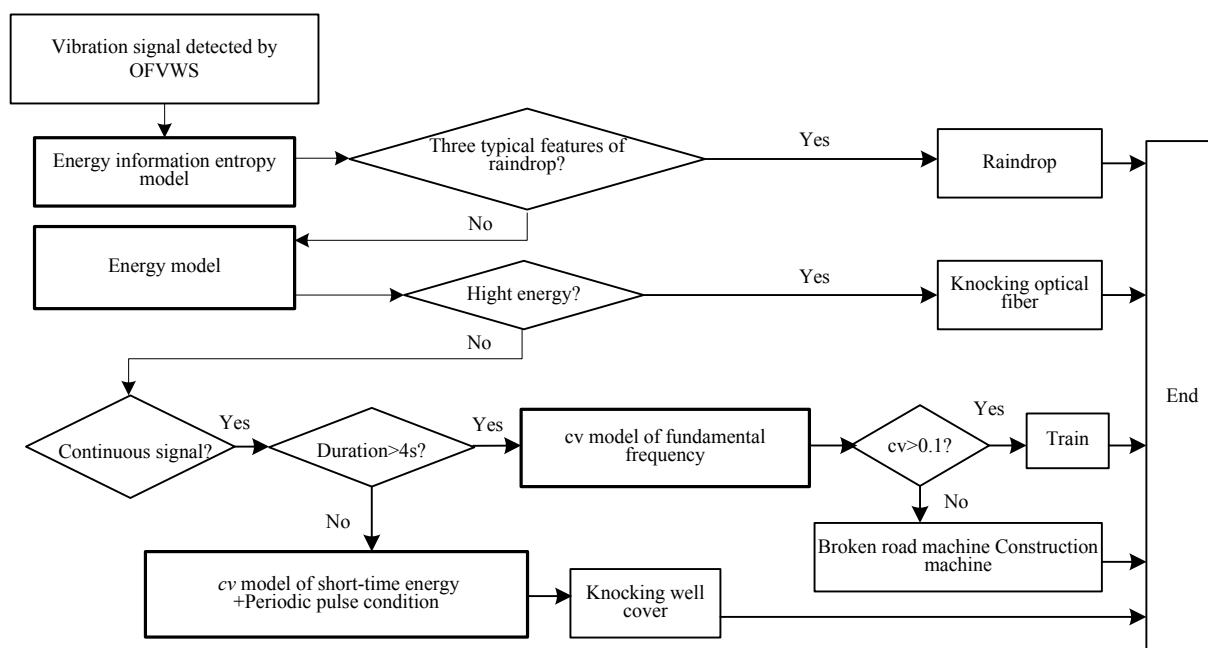

Fig. 6 Strategy for identifying vibration signals detected by OFVWS.

(2) Energy model

The energy model is used to judge if the detected vibration signals have high energy. If the detected vibration signals have high-energy feature, they will be the knocking optical fiber signals.

(3) Variation coefficient (cv) model of fundamental frequency

The duration time is judged for the continuous detected vibration signals. If the duration time is longer than 4 seconds, the cv model of fundamental

frequency will be used. If the calculated cv value is larger than 0.1, then the detected vibration signals are produced by a train, else they may be produced by a broken road machine or a construction machine.

(4) cv model of short-time energy and signal period

If the duration is less than 4 seconds, the cv model of short-time energy and signal period will be used. If the calculated cv value of short-time energy

is larger than 1 and the detected signals the satisfy periodic pulse condition, then the signals are produced by knocking well cover.

4.1 Energy information entropy model

An energy information entropy model is proposed to distinguish the raindrop vibration signal from the other vibration resource and extract two vibration signal features, uniform signal energy, and stable energy probability distribution based on the analysis of the attribute feature.

Based on the maximum entropy theorem, the maximum entropy value is given as follows:

$$H_{\max,k} = \log_b (n \cdot m) \tag{5}$$

where a two dimensional case is ($m \times n$). The energy information entropy of vibration signals in the kth minute is given as follows:

$$\bar{H}_k = H_k / H_{\max,k} = -\sum_{j=1}^{m} \sum_{i=1}^{n} p(x_{i,j}) \log_b p(x_{i,j}) / \log_b (n \cdot m). \tag{6}$$

Let $m=60$, $n=10$, and $p(x_{i,j})$ be the probability density function of p_k.

A conception of average distance D_k is used to reflect the stability of energy information entropy. D_k is defined as follows:

$$D_k = \sqrt{\frac{1}{\Delta l} \sum_{i=k-\Delta l}^{k} \left(\bar{H}_i - \bar{H}_{\text{ref}} \right)^2} \tag{7}$$

where $\bar{H}_i$ is the energy information entropy of vibration signal in the ith minute, $\bar{H}_{\text{ref}}$ is the reference value which is a statistical average value of a prior chosen segment of raindrop vibration signals, Δl is the length of statistical time, and D_k is the average distance of $\bar{H}_{\text{ref}}$ to a reference value. Variable coefficient cv_k of normalized energy information entropy is

$$\text{cv}_k = \frac{\sigma_k}{|\mu_k|} = \sqrt{\frac{1}{\Delta l} \sum_{i=k-\Delta l}^{k} \left(\bar{H}_i - \mu_k \right)^2} \bigg/ \left| \frac{1}{\Delta l} \sum_{i=k-\Delta l}^{k} \bar{H}_i \right| \tag{8}$$

where $\mu_k = \frac{1}{\Delta l} \sum_{i=k-\Delta l}^{k} \bar{H}_i$ is the average value of

$[k - \Delta l, k]$, and $\sigma_k = \sqrt{\frac{1}{\Delta l} \sum_{i=k-\Delta l}^{k} \left(\bar{H}_i - \mu_k \right)^2}$ is the standard deviation.

4.2 Fundamental frequency stability model

Every 20 frames vibration data of one-time vibration signals are divided into one group, then the short-time autocorrelation coefficient of each group can be calculated, and the fundamental frequency period can be extracted based on the position of a local peak of short-time autocorrelation coefficient. OFVWS is employed for an adaptive threshold to detect time intervals ΔT_i of two correlation coefficient peaks. The result is shown in Fig. 7.
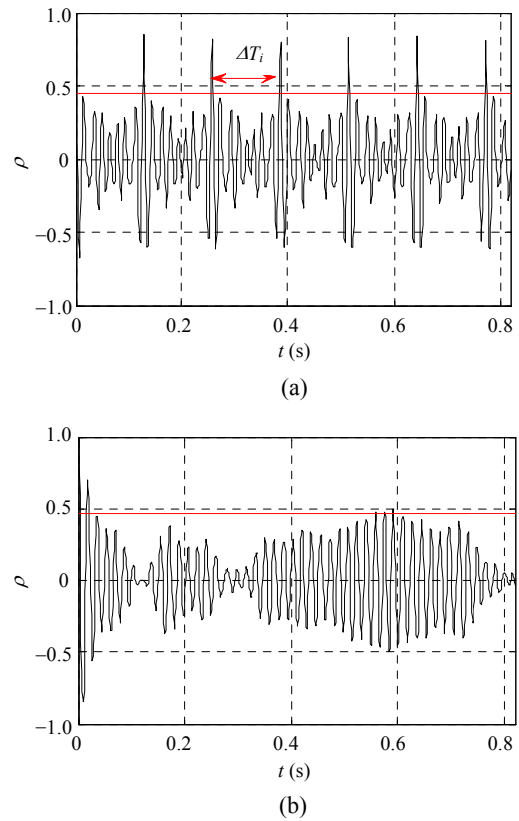

(a)

(b)

Fig. 7 Autocorrelation coefficients waveform of vibration signals.

The variable coefficient is defined as a specific value of standard deviation and mean value for random variable $X=\{x_1, x_2, \cdots, x_n\}$.

$$\text{cv} = \frac{\sigma}{|\mu|} \tag{9}$$

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$$\mu = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{10}$$

$$\sigma = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \mu)^2} \tag{11}$$

where μ and σ are the mean and standard deviations of the measurements, respectively.

There are four-group vibration signals by using the identification algorithm, and the result of recognition is shown in Fig. 8.
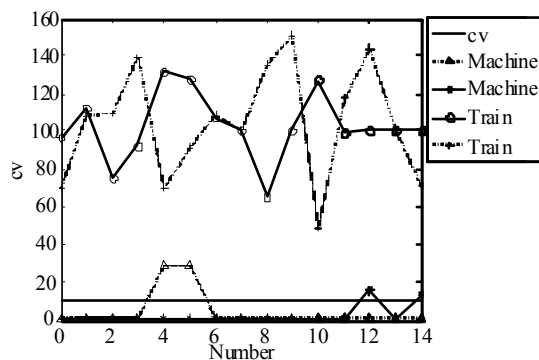

Fig. 8 Result of recognition.

From this figure, it can be observed that:

(1) Most of the variation coefficients of the mechanical vibration signals are stable and lower than cv_0.

(2) All of the variation coefficients of the train vibration signals are unstable and higher than cv_0.

(3) In the actual data, there are a large number of noise jamming, hence it can be determined as the mechanical vibration source as long as there exists one of the variation coefficients of fundamental frequency lower than the given threshold cv_0, and the coefficients which are above the threshold do not affect the final determination.

5. Conclusions

This paper mainly conducts on the attribute feature analysis of the vibration signals collected by OFVWS, and attribute feature models are established. The vibration source identification accuracy can be improved through the identification algorithm. Test results show that the design and selection of the feature models are reasonable, and the rate of identification is well. Future work will focus on increasing the library of signal features to achieve the identifying vibration sources in a wider range of operating environments.

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