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Method for Identifying Mechanical Vibration Source Based on Detected Signals by Optical Fiber

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Abstract: A Optical Fiber Vibration pre-Warning System (OFVWS) has an ability to detect and identify vibration signals by using a optical fiber cable lain along with pipes, hence it has been widely applied in some safety fields, such as the pipeline transportation, national defense, military base and so on. In the application of the OFVWS, one of the key issues is to identify harmful mechanical vibration sources quickly and efficiently. In this paper, we analyzed vibration signal produced by mechanical vibration sources and extracted the signal features transmitted by the OFVWS. A conclusion was drawn that most of mechanical vibration sources have an obvious feature of fundamental frequency. Based on this conclusion, we developed a method to detecting and recognizing a mechanical vibration source based on a variation coefficient of fundamental frequency periods. This method is able to accurately judge if the detected vibration signals having a feature of fundamental frequency or not by calculating and analyzing its variation coefficient of fundamental frequency periods. Field test results showed that this method can identify various harmful mechanical vibration sources, and have a high probability of detection and recognition, and a low probability of false alarm. *Copyright © 2013 IFSA.*

Keywords: Optical fiber sensor, Fundamental frequency, Mechanical vibration model, Variation coefficient.

1. Introduction

With the rapid development of pipeline transportation, the construction and ground-breaking around the pipeline can be seen everywhere, and they threaten the security of the pipeline seriously. The OFVWS can monitor the long-distance soil vibration information by using the fiber lain along with the pipeline as a distribute sensor. This system can warn the staff the destroying pipeline events happening as soon as possible, so it plays a role of safety early warning.

The common harmful mechanical vibration signals are generated by some working mechanical equipments and construction machines, such as the excavators, broken road machines and so on, which have a high power and exist for a long time. They have very high probability of damaging the pipeline and threaten the safety of the OFVWS seriously because they may break the surface of road and damage the fiber and pipeline quickly. Therefore, it is a key to detecting and identifying a mechanical vibration source accurately and quickly by using the OFVWS.

At present, researches on the recognition of vibration signals include: linear classifiers [1], neural network [2], support vector machines [3, 4], etc. These methods all need to study and train on a large number of samples, hence have some issues, such as a large amount of calculation and a convergence of training.

In addition, there also exist some harmless interfering vibration sources in the fiber-optic warning area even through their power are high and their duration time are long, for example, a train passing vibration source. These vibration sources just pass through the area covered by optical fiber frequently, and do not generate any harmful action to threat the warning area. However, conventional vibration detection method might confuse these harmless vibration sources with the harmful mechanical vibration sources so as to send the staffs a false alarm of harmful vibration source frequently. This can influence the recognition badly, and is unfavorable for the reliability of the system running.

In this paper, a method to identifying mechanical source is presented by using a vibration source feature model and the detected vibration signal data by the OFVWS. This method can distinguish between a harmful mechanical vibration source and a harmless train vibration source, and identify the mechanical vibration source automatically without using a learning and training process. Therefore, its amount of computation is reduced greatly. This method can reduce the probability of error identification by improve the correct recognition probability.

2. Working Principle of OFVWS

Fig. 1 shows the working principle of a vibration source measuring and locating system [4]. A distributed optical fiber sensor, which is laid along with the pipeline, can detect a vibration signal along the pipeline.

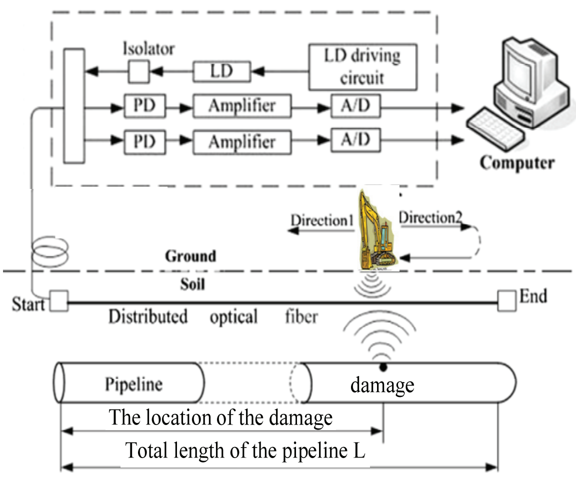


Fig. 1. Working principle of OFVWS.

The detected vibration signals will be transported by the optical fiber sensor to photoelectric detectors, and then is transmitted through photoelectric conversions, Amplifications and AD conversions, and finally to a computer for further process and analysis. In this way, the OFVWS can monitor the vibration signals in its coverage areas in real-time.

The sampling frequency of the OFVWS is 25 kHz and every 1024 sampling data form a frame. Because of an interference caused by low frequency signal and high frequency signal in the signal transmission, such as the power supply (220 V, 50 Hz), the OFVWS uses an 800-order FIR band-pass filter to pre-process all the collected data. Its pass-band range from 100 Hz to 3 kHz and its frequency response is shown in Fig. 2.

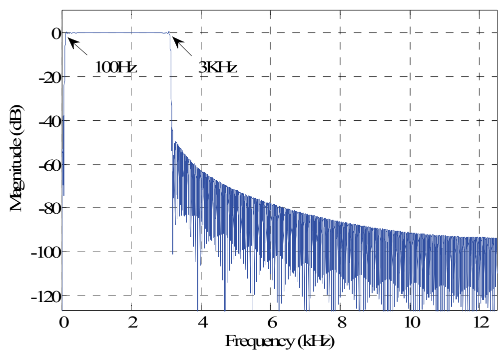


Fig. 2. Frequency response of the FIR filter.

3. Time and Frequency Domain Analysis of Vibration Signal

Generally, a vibration source will turn to be a harmful vibration source when the power of signal is high enough and its duration time is long enough. However, there exist two kinds of this vibration sources which have the above features in the nature, one may be a passing train, and another be a working construction machine. The former vibration source does no harm to a safety of the pipeline and the OFVWS, hence it dose not need to send alarm to the safety staffs. But the later may be harmful. Therefore, it is very important to distinguish between the train vibration signal and the mechanical vibration signal.

The traditional vibration signal analysis method is a time domain and frequency domain analysis. Here, we also use this method to analyze a mechanical vibration signal and a train vibration signal detected from some oil pipelines, respectively.

3.1. Signal Power and Time-domain Waveform Analysis

We analyze the signal power by using one-minute vibration signal data and calculate their single power, as shown in Fig. 3. Then we choose 20 frames data (about 0.8 seconds), which have relative higher power than the other chosen signal. We will analyze their amplitude and observe their time-domain waveforms. Fig. 4(a) and Fig. 4(b) show the time-domain waveforms of the corresponding mechanical and train vibration signals.

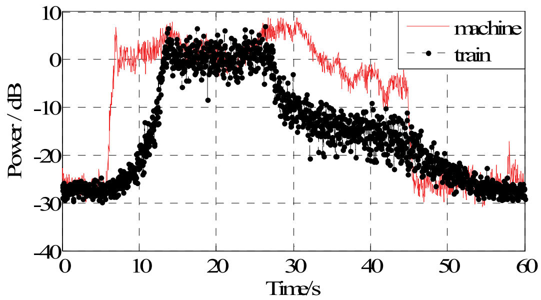
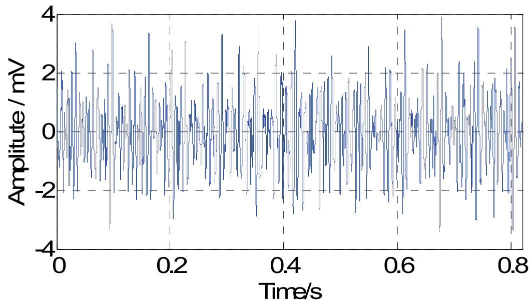
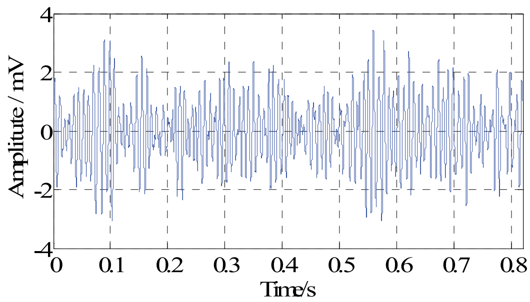


Fig. 3. Single power analysis results.



(a) Mechanical vibration signals.



(b) Train vibration signals.

Fig. 4. Time-domain waveforms.

From Fig. 3-4 we can observe that:

(1) The signal power and duration time of the mechanical and train vibration source are very similar. It is very difficult to distinguish them by using the signal power feature, as shown in Fig. 3.

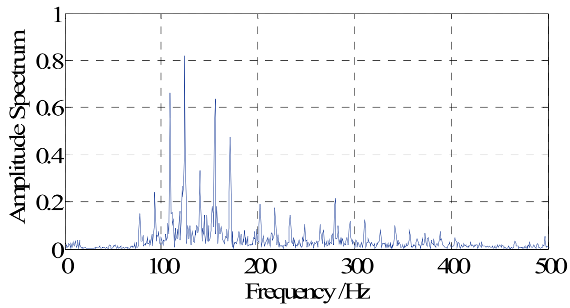
(2) Their time-domain waveforms in Fig. 4(a) and Fig. 4(b) are also very similar, and their amplitudes are about 2 mV.

A conclusion can be drawn that it is difficult to distinguish between the mechanical and train vibration signals by only using signal power and time-domain waveform analysis.

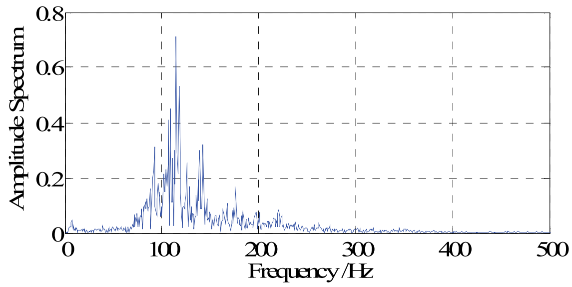
Next, we will analyze their frequency features of these vibration signals.

3.2. Fundamental Spectrum Analysis

Because the low frequency part of signals is filtered by the band-pass filter as shown in Fig. 2, the signals lower than 100 Hz frequency are filtered. The frequency of filtered data is as shown in Fig. 5.



(a) Mechanical vibration signals.



(b) Train vibration signals.

Fig. 5. Frequency spectrum analysis.

We can observe a difference between these signals from Fig. 5. The frequency spectrum of the mechanical vibration signals contains multiple discrete spectral lines, and the intervals between adjacent spectral lines are almost a fixed value. This feature is clearly different from the train vibration signals. Therefore, a mechanical signal has a periodical change feature. We infer that this feature can be used as a basis to distinguish between the mechanical and train vibration signals.

4. Feature Extraction of Mechanical Vibration Source

In section 3, we infer that the studied harmful vibration signals have a periodical change feature in its frequency spectrum. We can use a complex periodic mechanical signal model to represent the studied signal [5-7], as shown in Equation (1):

$$x(t)=\sum_{n=1}^{\infty}A_n\cos(2\pi nft-\theta_n)\,, \tag{1}$$

where x is the amplitude of a vibration signal; f is the fundamental frequency of a vibration signal, which can represent a feature of spectral line intervals, Hz; A_n and θ_n are the amplitude and an phase of the nth Harmonic waves, respectively; t is the time, s; n is the order of harmonic wave.

For the studied vibration signals, we suppose n=13, f=15 Hz, and then obtain the simulation results, as is shown in Fig. 6(a) and Fig. 6(b). The simulation signals are processed by a band-pass filter further, as shown in Fig. 6(c) and Fig. 6(d).

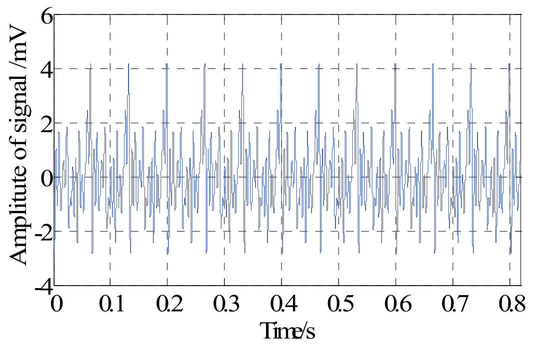


Fig. 6 (a). Frequency domain waveform of the simulated mechanical vibration signals.

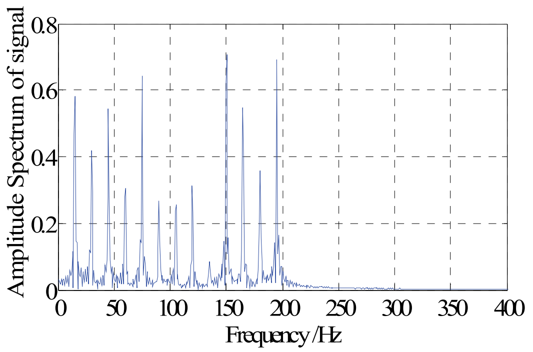


Fig. 6 (b). Frequency domain waveform of the simulated mechanical vibration signals.

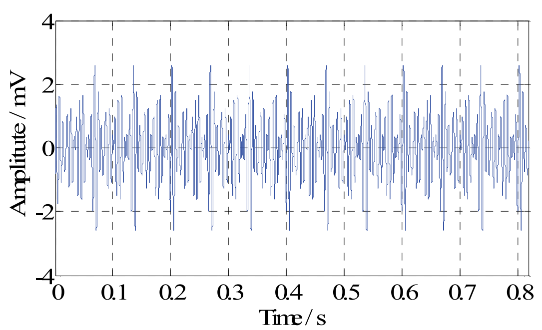


Fig. 6 (c). Frequency domain waveform of the filtered vibration signals.

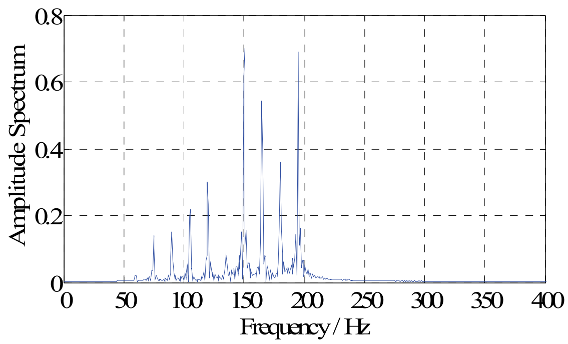


Fig. 6 (d). Frequency domain waveform of the filtered vibration signals.

Comparing Fig. 4(a) and Fig. 6(c), Fig. 5(a) and Fig. 6(d), separately, we can know that the identification model, as shown in Equation 1, is correct. Therefore, we can extra the feature of fundamental frequency of signal, f, to identify a harmful mechanical vibration source. If a vibration signal has its fundamental frequency feature, then it is inferred to be a mechanical vibration signal; otherwise to the contrary.

5. Mechanical Vibration Source Identification Method

From the above analysis, we know that the key of identification is to extract a fundamental frequency feature of vibration signals. Therefore, we will develop a method to identify a kind of high-power mechanical vibration source existing for long time. The presented method is based on a variation coefficient of fundamental frequency. First, we will extract fundamental frequency information of vibration signals from their autocorrelation coefficients. From this result, we can infer if the vibration signals have fundamental frequency feature or not. Second, we measure the stability of fundamental frequency periods by calculating a variation coefficient of peak value intervals in an autocorrelation coefficient curve. This index can directly reflect if the curve having a periodicity or not. At last, we establish a strategy to identify a mechanical vibration source automatically.

5.1. Extraction of Fundamental Frequency Information

Autocorrelation is the cross-correlation of a signal with itself, and it can find repeating patterns, such as the presence of a periodic signal which has been buried under noise, or identifying the missing fundamental frequency in a signal implied by its harmonic frequencies. Therefore, we use the autocorrelation coefficient to extract fundamental frequency information.

The sampling frequency of the OFVWS system is 25 kHz, which means a huge calculation load. In order to reduce the amount of calculation, we use a down-sampling method to sample the vibration signal data. $X=\{x_1 \ldots x10 \ldots x20 \ldots x30 \ldots x20n\}$ represents an observed vibration signal sequence and its length is $20\times n$. We down-sample signal data X from every 10 samples. The down-sampling of X is Y:

$$Y=\{y_1,y_2,y_3,\ldots,y_{2n}\}=\{x_{10},x_{20},x_{30},\ldots,x_{20n}\}, \tag{2}$$

where Y is the observed down-sampled sequence of X and its length is $2\times n$.

We can obtain a short-time autocorrelation coefficient [8] of Y with Equation (3):

$$R(k)=\frac{\sum_{i=1}^{n}\left(y_i-\frac{1}{n}\sum_{m=1}^{n}y_m\right)\left(y_{i+k}-\frac{1}{n}\sum_{m=k+1}^{n+k}y_m\right)}{\sqrt{\sum_{i=1}^{n}\left(y_i-\frac{1}{n}\sum_{m=1}^{n}y_m\right)^2}\sqrt{\sum_{i=1}^{n}\left(y_{i+k}-\frac{1}{n}\sum_{m=k+1}^{n+k}y_m\right)^2}} \tag{3}$$

where k=1,2,...,n, R is the short-time autocorrelation coefficients and $R=\{r_1, r_2,\ldots, r_n\}$.

By using Equation (3) we can obtain $R(k)$, $1\le k\le n$. A autocorrelation coefficient curve figure of $R(k)$ can be formed. In this curve figure, there will be some local maximal peaks. Here we record the number of these local maximal peaks, d, and the time interval of the adjoined two maximal peaks, ΔT. A time interval sequence will be obtained, $\Delta T=\{\Delta T_1, \Delta T_2,\ldots, \Delta T_{d-1}\}$.

The coefficient of variation is a statistical magnitude which is used to measure the degree of variation of the measurement value. The value of the coefficient of variation can illustrate the degree of dispersion of the samples. The smaller of the value means the smaller degree of variation of the measured values, which means more stable of the measured value. Since the coefficient of variation is a dimensionless number, it can represent the significance level of the local maximal peak intervals of the autocorrelation coefficients. Hence this index can directly reflect if the observed vibration signals having a periodicity or not. The formula of a coefficient of variation [9, 10] is defined as follow:

$$cv=\frac{\sigma}{|\mu|}\times 100\%, \tag{4}$$

$$\mu=\frac{1}{d-1}\sum_{i=1}^{d-1}\Delta T(i) \tag{5}$$

$$\sigma=\sqrt{\sum_{i=1}^{d-1}[\Delta T(i)-\mu]^2}, \tag{6}$$

where cv is the μ coefficient of variation of the measurements, and σ are the mean and standard deviation of the measurements, respectively; d-1 is the number of the measurements.

5.2. Implementation of Identification Strategy

We establish a strategy to identify a vibration source by using Equation 2-6. Fig. 7 shows the implementation of this identification strategy.

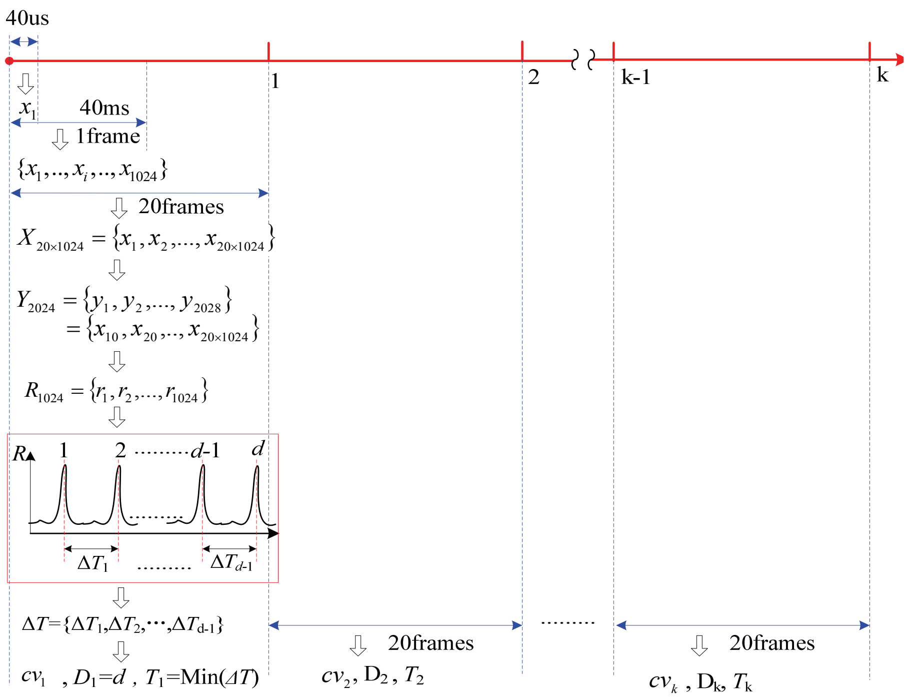


Fig. 7. Implementation of identification strategy.

The steps of the strategy are as follows:

(1) The OFVWS detects a vibration signal, x_1, every *40 μs*. Every 1024 data of the signals comprise one frame. The signal power (P_1) and the duration time ($Time_1$) for these vibration signals will be calculated. Only when P_1 and $Time_1$ are both bigger than their thresholds, P_0 and $Time_0$, respectively, then the presented identification strategy is started. We will process the vibration signal data every 20 frames (about 0.8 s), that is, $X=\{x_1, x2... x20_{\times 1024}\}$.

(2) Down sample the signal data $X=\{x_1, x2... x20_{\times 1024}\}$ with Equation (2), and obtain its down-sampled sequence, $Y=\{y_1, y2... y2048\}$ in this 20 frames.

(3) Calculate the short-time autocorrelation coefficients of Y, and obtain the corresponding short-time autocorrelation coefficient sequence, $R=\{r_1, r_2... r_{1024}\}$, and a curve figure of R will be formed. From this curve, we can observe the number of the frequency spectrum intervals, d, and $\Delta T=\{\Delta T_1, \Delta T2,..., \Delta T_{d\text{-}1}\}$ by setting the autocorrelation coefficient threshold as a floating value. Let $D_1=d$. The minimum interval of the periodical frequency spectrum is the minimum value of ΔT, that is, $T_1=Min(\Delta T_1, \Delta T_2,..., \Delta T_{d\text{-}1})$. Only when D_1 and T_1 are both larger than their set values d_0 and T_0, respectively, the presented identification strategy is continued.

(5) Calculate the variation coefficient of the intervals $\Delta T=\{\Delta T_1, \Delta T_2,..., \Delta T_{d\text{-}1}\}$ for this 20 frames, that is, cv_1.

(6) Repeat the above step (1)-(5) to process the other 20-frame signals, then a variation coefficient sequence will be formed, $CV=\{cv_1,cv_2,...,cv_k\}$.

(7) If the minimum value of $\{cv_1,cv_2,...,cv_k\}$ is less than a given threshold value, cv_0, then this indicates that the vibration signals have a periodicity and are generated by a mechanical vibration source. Otherwise it is not a mechanical one.

5.3. Identification Results

We analyze four kinds of signal data collected by the OFVWS from the pipeline of the China Petroleum Pipeline Bureau. The signal data of 'machine$_1$' and 'machine$_2$' are two different kinds of mechanical vibration signals. One was produced by an excavator and the other by a broken road machine. The signal data of 'train$_1$' and 'train$_2$' were produced by trains passing through the Lan-Zheng-Chang oil pipeline.

We will process these vibration signals by using the presented identification method, and evaluate its reliability. The autocorrelation coefficients waveforms of the mechanical and train vibration signals are shown in Fig. 8(a) and Fig. 8(b), respectively, and Fig. 8(c) and Fig. 8(d) show the intervals extracted in the autocorrelation coefficients of the mechanical and train vibration signals.

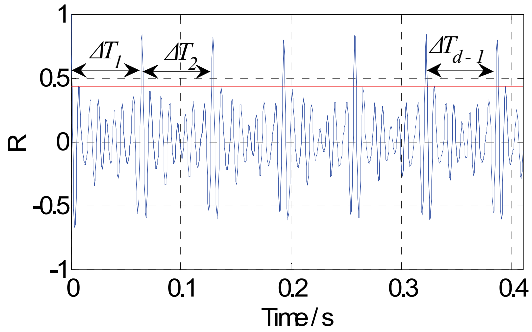


Fig. 8(a). Autocorrelation coefficients waveform of vibration signals and their intervals for mechanical vibration signals.

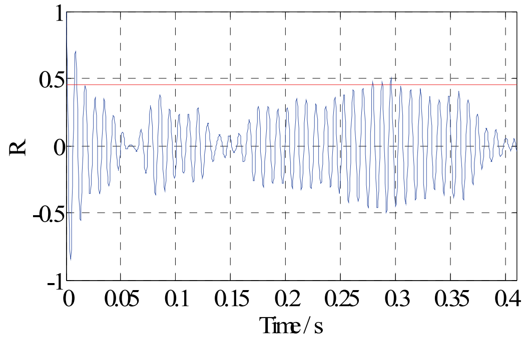


Fig. 8(b). Autocorrelation coefficients waveform of vibration signals and their intervals for train vibration signals.

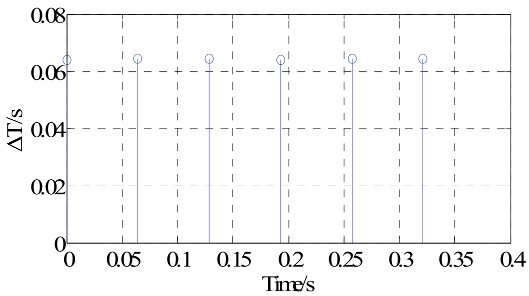


Fig. 8(c). Autocorrelation coefficients waveform of vibration signals and their intervals, extracted in the mechanical signals.

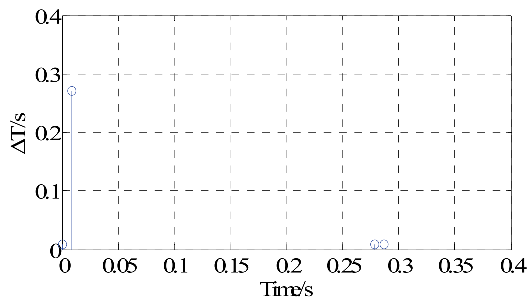


Fig. 8(d). Autocorrelation coefficients waveform of vibration signals and their intervals, extracted in the train signals.

From Fig. 8 we can observe that: the short-time autocorrelation coefficients of mechanical vibration signals have a stable periodicity, which is obviously different from the train vibration signal. We can extract the fundamental frequency period, $\Delta T=\{\Delta T_1, \Delta T_2,\ldots, \Delta T_{d-1}\}$, with a suitable set threshold, as shown in Fig. 8(a).

Then we can calculate a variation coefficient (cv_k) of the fundamental frequency intervals to measure the fundamental frequency stability of vibration signals. We set the power threshold, P_0, as -20 dB, and the duration time threshold, T_0, as 4 seconds. After extracting the local maximal peak intervals of the autocorrelation coefficients, we set d_0=5 and T_0=60 s, respectively. The floating threshold will adapt itself in order to obtain the effective intervals and let cv_0=10. Fig. 9 shows the results of cv.

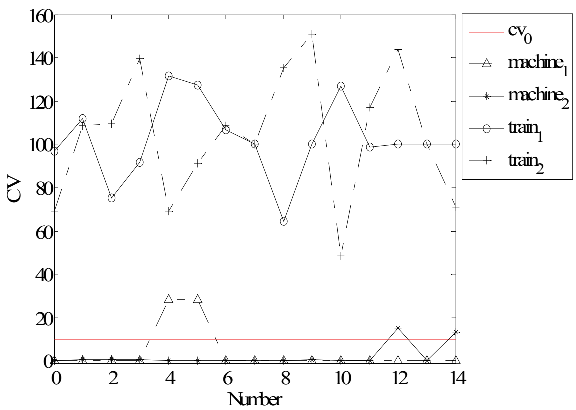


Fig. 9. Result of recognition.

From Fig. 9, we can observe 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) There are a large number of redundancy in the actual data, hence it can be determined as mechanical vibration source as long as there exists one of the variation coefficient of fundamental frequency lower than the given threshold cv_0, and the coefficients which are above the threshold don't affect the final determination.

From the above studies, we can conclude that this identification strategy can detect and identify mechanical vibration signals accurately.

6. Conclusions

For the safety of pipeline running, it might be harmful for a kind of vibration source, which has high vibration power and exists for long time. A frequently passing vehicle, such as a passing train, also has these features, but this vibration source is harmless. At this time, an OFVWS will send the staff a false alarm, which will decrease the working reliability of the OFVWS badly.

In order to improve the identification performance and reduce the probability of false alarm for the OFVWS, we analyzed the fundamental frequency features of the vibration signals, and present a method for identifying harmful mechanical vibration sources, which have high power and long existing duration. This method can extract the fundamental frequency periods of the vibration signals, then evaluate its stability by calculating the variation coefficients of fundamental frequency periods (cv), and finally identify the harmful mechanical vibration sources from the other vibration sources.

In order to investigate the performance of the presented method, we process some vibration signal data detected by an OFVWS of the China Petroleum Pipeline Bureau. The results show that this method can distinguish the harmful mechanical vibration sources accurately from the high-power and long-duration sources by analyzing the stability of variation coefficients of fundamental frequency.

This presented method based on the variation coefficients of the fundamental frequency periods can identify the harmful mechanical vibration sources accurately in real-time and reduce the false alarm rate. At the same time, it needn't a process of learning and training, so can reduce the calculation amounts greatly.

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