www.sensorsportal.com

Sensors & Transducers

http://www.sensorsportal.com

Approach to Identifying Raindrop Vibration Signal Detected by Optical Fiber

Hongquan QU, Shouwen LIU, Yongjiao WANG, Guoxiang LI
College of Information Engineering, North China University of Technology, Beijing, 100041 China
Tel.: +86-10-82313186, fax: +86-10-82316654
E-mail: qhqphd@163.com

Received: 23 September 2013 /Accepted: 22 November 2013 /Published: 30 December 2013

Abstract: Optical Fiber Vibration pre-Warning System (OFVWS) is widely applied to pipeline transportation, defense boundary and military base. One of its key technologies is signal feature extraction and vibration source identification. However, some harmless vibration signals often affect the reliability of this identification process due to the false alarms. Therefore, it is very important to identify various harmless vibration signals effectively. In this paper, we analyze the energy distribution feature of nature raindrop vibration signal detected by optical fiber. Based on this analysis, we develop an energy information entropy model and an approach to identify the harmless raindrop vibration signal. Study shows that the nature raindrop vibration signal can be detected and identified automatically by extracting the energy information entropy value and combining with the statistical detection method. The field tests result also showed that this approach based on energy information entropy model is able to effectively identify harmless raindrop vibration signal. Its identification probability is high and its false alarm and false recognition probability is low, hence the working performance of the OFVWS can be improved by using the presented approach. *Copyright © 2013 IFSA.*

Keywords: Fiber vibration sensors, Information Entropy, Feature extraction, Vibration signal, Variation coefficient.

1. Introduction

With the rapid development of pipeline transportation, some constructions often happen along the pipeline and will threaten the security of pipeline seriously. It needs some active means of defense to ensure the safety of pipe. The OFVWS uses the optical fiber cable laid along the pipeline as distribution sensors to detecting various vibration signal [1-3]. Fig. 1 shows a schematic diagram of the OFVWS. The optical cable lain along the pipeline can obtain vibration signal by using distributed vibration signal sensor [4-7]. When a vibration source appears, it produces mechanical vibration signal, which is transmitted by the optical fiber to a photodetector sensor, and then to the computer after the photoelectric conversion and analog-to-digital conversion. The computer analyzes these vibration signals. In this way, the OFVWS can realize real-time monitoring and alarming. Sampling frequency of photodetector is 25 kHz. A 800-order FIR band-pass filter is often used to filter and process the sample data. It can overcome signal interference produced by other low-frequency and high-frequency signal during signal transmission process. Its passband range is 100 Hz to 3 kHz.

In the pipeline running, there are various vibration signals. Some of these are harmful and they might be produced by electrical drills, broken road machines, human destroying optic fiber cable, large-scale construction machines, and so on. Some are harmless and might be produced by human knocking the well covers, rain dropping into the well, train, car, and so on. These harmless vibration sources will not threaten the safety of the pipeline, but their vibration signals produced by these sources will interfere with the identification performance for the harmful source because they will cause badly false alarm. Therefore, it is very important to accurately identify these harmless vibration sources. It is one of the keys for the OFVWS [8].

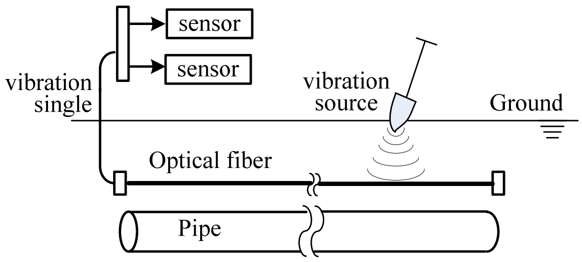

Fig. 1. Schematic diagram of OFVWS.

The current methods to identifying the vibration signal of optical fiber include linear classifiers, neural network methods, analysis of variance, chaos analysis, SVM-based recognition method [9-15]. But these methods have in a common feature, that is, they need a large number of samples for learning and training, hence the computation load is heavy, and there is still convergence issue in its practical application.

In this paper, we present an approach to identify raindrop vibration signal detected by optical fiber based on an energy information entropy model and a variation coefficient. This approach can extract the main signal features of raindrop (uniform signal energy and stable energy probability), hence it can identify a raindrop vibration signal effectively. In addition, it does not need a training process, hence its computation load is very small.

2. Pre-analysis of Typical Vibration Signals

2.1. Spectrum Analysis

In an actual pipe running, vibration signal is often generated by some typical sources, such as raindrop, electrical drill, broken road machine, human knocking a well cover or optic fiber cable, large-scale construction machine, train and so on. The conventional method to processing the vibration signals is to use the spectrum analysis, which transfers complex vibration signals from the time domain into the spectrum domain, so as to extract some expectant features for source identification.

In this section, we analyze some vibration signals monitored by the OFVWS from some oil pipelines of the China Petroleum Pipeline Corporation by using the spectrum analysis method. Fig. 2 shows the spectrum analysis results of vibration signals generated by raindrop, broken road machine, large-scale construction machine, human knocking well cover or optical fiber cable.

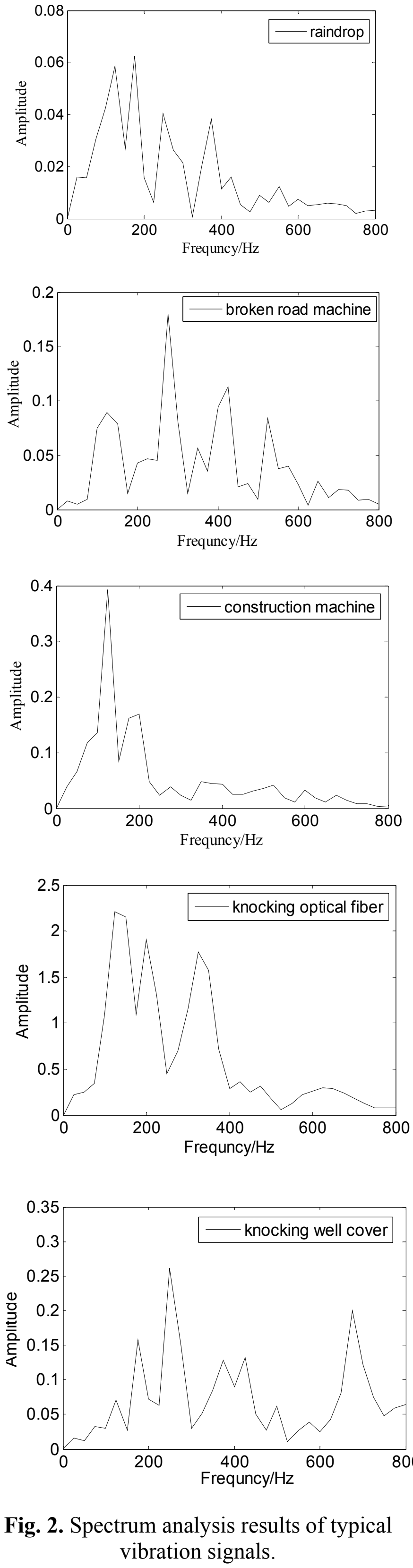

Fig. 2. Spectrum analysis results of typical vibration signals.

From Fig. 2 we can observe that: their frequency band is similar in spectrum domain, hence it is difficult to distinguish between the harmless raindrop vibration signal and the other harm vibration signals. This will cause false alarm and reduce the working reliability of the OFVWS. Therefore, it is impossible to identify a raindrop signal by using the spectrum analysis. It needs to develop the other method to extract the features of raindrop signal.

2.2. Signal Energy Analysis

In this section, we analyze the features of the above vibration signals by using signal energy analysis method. Based on this, we will develop an approach to identify harmless raindrop vibration source.

The signal energy per frame (1024 sampling data in 40 ms) can be calculated with Eq. (1):

$$w_j = 10\log_{10}\left(\sum_{i=1}^{1024} x_i^2\right), \tag{1}$$

where w_j is the signal energy in the j^{th} frame, dB; x_i is the amplitude of i^{th} detected vibration signal.

Fig. 3 shows signal energy scatter plots produced by a raindrop, a broken road machine, a large-scale construction machine, human knocking well cover and optical fiber cable, respectively. In this Fig., the abscissa is the number of time sequence frame, and the ordinate is the signal energy per frame, w_j.

The signal energy is divided into 10 intervals from -20 dB to 10 dB, and then the frequency of signal energy per frame can be statistically calculated in per interval. In this way, we can obtain the discrete probability density function of signal energy, as shown in Fig. 4.

From Fig. 3~4, we can observe that:

1) The vibration signal energy of nature raindrop has three typical features, that is, uniform signal energy, stable energy probability distribution, and vibration existing stable for a long time.

2) The other signals did not have these three features in the same time.

It is easy to extract the third feature (vibration existing stable for a long time), hence we just focus on developing a statistical model to extract the other two features of raindrop vibration signal.

3. Energy Information Entropy Model

In this section, in order to identify the harmless raindrop vibration source, we will develop an energy information entropy model and use this model to extract the two vibration signal features, uniform signal energy and stable energy probability distribution.

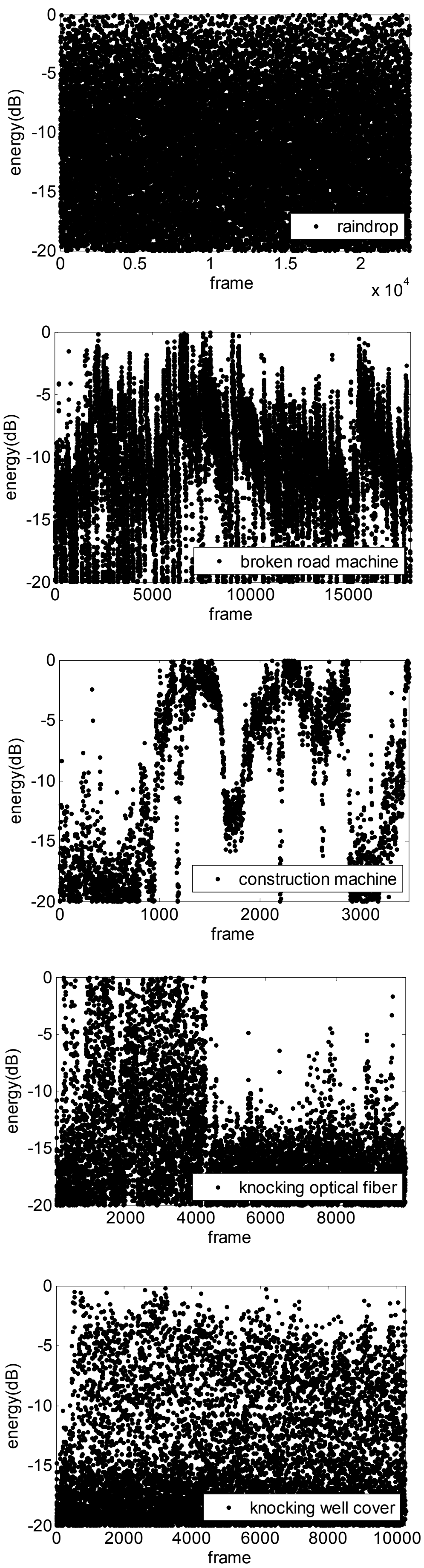

Fig. 3. Signal energy scatter plots.

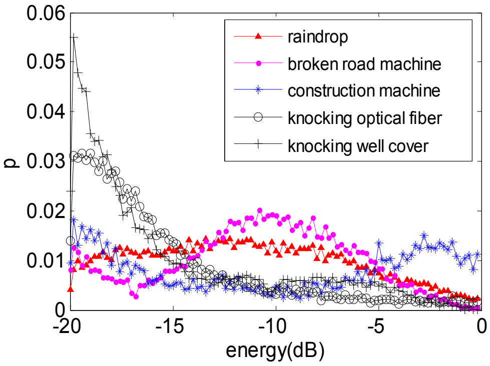

Fig. 4. Discrete probability density function of signal energy.

3.1. Information Entropy

In information theory, entropy is used to measure an expectation of a random variable appearing. It represents the amount of loss information in the transmission process before it is received. It is also known as information entropy or Shannon entropy. The information entropy H of a random variable, $\{x_1, x_m, \cdots, x_{m_{\max}}\}$, can be defined in Eq. (2):

$$H(X) = -\sum_{m=1}^{m_{\max}} p(x_m)\log_2 p(x_m) \tag{2}$$

where p is the probability density function of $\{x_1, x_m, \cdots, x_{m_{\max}}\}$; $m_{\max}$ is the number of the first dimension.

For a two dimensional case ($m \times n$), the information entropy of $\{x_{1,1}, x_{m,n}, \cdots, x_{m_{\max}, n_{\max}}\}$ can be calculated with Eq. (3) [16]:

$$H(X) = -\sum_{n=1}^{n_{\max}} \sum_{m=1}^{m_{\max}} [p_{m,n} \log_2(p_{m,n})] \tag{3}$$

where $n_{\max}$ is the number of the second dimension.

The magnitude of information entropy is closely related to its probability density function. If its probability density is uniform distribution, then its information entropy will reach the maximum value.

3.2. Energy Information Entropy Model for Vibration Signal

Base on the concept of information entropy, energy information entropy model for vibration signal detected by the OFVWS can be developed further, as shown in Eq. (4).

$$H_W^k = -\sum_{n=1}^{n_{\max}} \sum_{m=1}^{m_{\max}} [p_{m,n} \log_2(p_{m,n})] \tag{4}$$

where H_W^k is the energy information entropy of vibration signal in the k^{th} minute; $p_{m,n}$ is the probability density function of w_j.

In order to obtain energy information entropy of vibration signal per minute, H_W^k, we will calculate the probability density function of w_j, $p_{m,n}$:

According to the distribution of the signal energy, we set intervals on the energy axis, which is divided into $m_{\max}$ intervals from -20 dB to 0 dB, here let $m_{\max}$ =10. On the frame axis, it is divided into $n_{\max}$ intervals with a fixed frame step, here let $n_{\max}$ =60 frame. In this way, a two-dimensional space, energy-frame, can be divided into $m_{\max} \times n_{\max}$ grids, as shown in Fig. 5. We can account the number of energy data in every grid, and obtain the probability, $p_{m,n}$, in every grid. If there is no energy data in a grid, then it represents this grid interval has no contribution to the calculation of energy information entropy, hence $p_{m,n}\log_2(p_{m,n}) = 0$

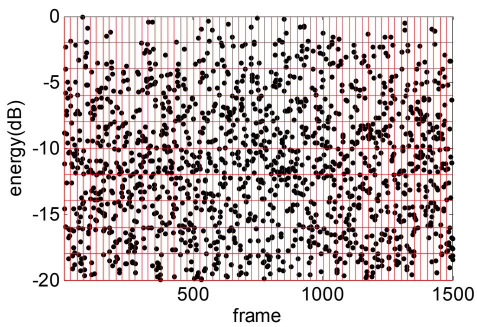

Fig. 5. Divided energy-frame space for one minute.

After obtaining the probability distribution, the energy information entropy per minute, H_W^k, can be calculated with Eq. (4).

The maximum entropy value will appear when all probabilities in all grids are same:

$$H_{W,\max} - \sum_{n=1}^{n_{\max}} \sum_{m=1}^{m_{\max}} [p_{m,n} \log_2(p_{m,n})] = \log_2(m_{\max} \cdot n_{\max}) \tag{5}$$

In order to compare the results, we will normalize the energy information entropy per minute by divided by $H_{W,\max}$:

$$\overline{H}_W^k = \frac{H_W^k}{H_{W,\max}} \tag{6}$$

3.3. Stability of Energy Information Entropy

We can adopt two methods to assess the stability of energy information entropy.

1) Average distance of $\overline{H}_W^k$

We can use a conception of average distance, D, to reflect the stability of energy information entropy. D is defined as follows:

$$D = \sqrt{\sum_{k=l}^{l+\Delta l} \left(\overline{H}_W^k - \overline{H}_W^{ref} \right)^2} \tag{7}$$

where D is the average distance of $\{\overline{H}_W^l,..,\overline{H}_W^k,..,\overline{H}_W^{l+\Delta l}\}$ to a reference value, $\overline{H}_W^{ref}$ in time interval $[l, l+\Delta l]$; $\overline{H}_W^{ref}$ is the reference value and is a statistical average value of a prior chosen segment of raindrop vibration signals.

It is important to choose a reasonable value of $\overline{H}_W^{ref}$. By analyzing our prior known raindrop vibration signals, we let $\overline{H}_W^{ref}$=0.94.

2) Variation coefficient of $\overline{H}_W^k$

We can also adopt a variation coefficient to reflect the stability of energy information entropy. The variation coefficient (C_V) is a normalized measure of dispersion of a probability distribution. The absolute value of C_V is sometimes known as relative standard deviation, which is expressed as a percentage. C_V is defined as the ratio of the standard deviation to the mean:

$$C_V^l = \frac{\sigma_H^l}{\left| \mu_H^l \right|} \tag{8}$$

where C_V^l is the variation coefficient of $\{\overline{H}_W^l,..,\overline{H}_W^k,..,\overline{H}_W^{l+\Delta l}\}$ in time interval [l, l+Δl]; μ_H^l is the mean, $\mu_H^l = \frac{1}{\Delta l}\sum_{k=l}^{l+\Delta l}\overline{H}_W^k$; σ_H^l is the standard deviation, $\sigma_H^l = \sqrt{\sum_{k=l}^{l+\Delta l}\left(\overline{H}_W^k - \mu_H^l\right)^2}$.

The smaller C_V^l is, the smaller the variation degree of $\{\overline{H}_W^l,..,\overline{H}_W^k,..,\overline{H}_W^{l+\Delta l}\}$ will be, and the more stable this variable will be.

4. Approach to Identifying Raindrop Vibration Source

4.1. Identification Process

The normalized energy information entropy of vibration signal ($\overline{H}_W^k$), the average distance (D_l) and the variation coefficient (C_V^l) are able to reflect the two features, the uniform signal energy and the stable energy probability distribution. We can use Eq. (4), (7) and (8) to extract these two features of raindrop vibration signal detected by optical fiber. We will develop an identification approach to obtain these parameters. This approach will be explained with an example, in which the identification time is 16 minutes, as shown in Fig. 6. The approach is realized as following:

1) Every 40 μs, the OFVWS samples a vibration signal, x_i.

2) In one frame (40ms), there will be 1024 signal vibration data. A signal data set, $\{x_1,...,x_i,...,x_{1024}\}$, can be formed in every 40 ms. Correspondingly, we can calculate the signal energy, w_j, in this frame with Eq. (1).

3) In one minute, there will be 1500 frames, hence there will be 1500 signal data sets and their corresponding signal energy set, $\{w_1,..., w_j,..., w_{1500}\}$.

We divide the 2-dimentional space of energy-frame by letting $\Delta w = 2$ dB and $\Delta \text{frame} = 25$ frame. The energy-frame space is divided into 10×60 grids ($m_{\max}$=10 and $n_{\max}$=60), as shown in Fig. 5. The probability distribution of energy per minute, $\{p_{1,1},..., p_{m,n},..., p_{10,60}\}$, can be obtained. Hence we can calculate the energy information entropy of vibration signal per minute, H_W^1, with Eq. (4) and its normalized value, $\overline{H}_W^1$.

4) From 1 to 10 minutes (let Δl=10min), there will produce 10 energy information entropies of vibration signal, $\{\overline{H}_W^1,...,\overline{H}_W^k,...,\overline{H}_W^{10}\}$, then we calculate one average distance, D_1, by using $\overline{H}_W^{ref}$. We can also calculate one variation coefficient, C_V^1. In this way, we obtain the other D_l and C_V^l in every 10 minute interval.

5) At last, a normalized energy information entropy set, $\{\overline{H}_W^1,...,\overline{H}_W^k,...,\overline{H}_W^{16}\}$, an average distance set, $\{D_1,...,D_l,...,D_7\}$ and a variation coefficient set, $\{C_V^1,...,C_V^l,...,C_V^7\}$, are formed.

We set two thresholds, D_0 and C_{V0}, to judge if the vibration signal detected by the OFVWS is produced by a raindrop source or not. The criterion is as shown in Eq. (8):

$$\begin{cases} D_l < D_0 \\ C_V^l < C_{V0} \end{cases} \tag{9}$$

If the vibration signal satisfies Eq. (9), then it is produced by a harmless raindrop source and it does not need alarm; otherwise, it is produced by other vibration source.

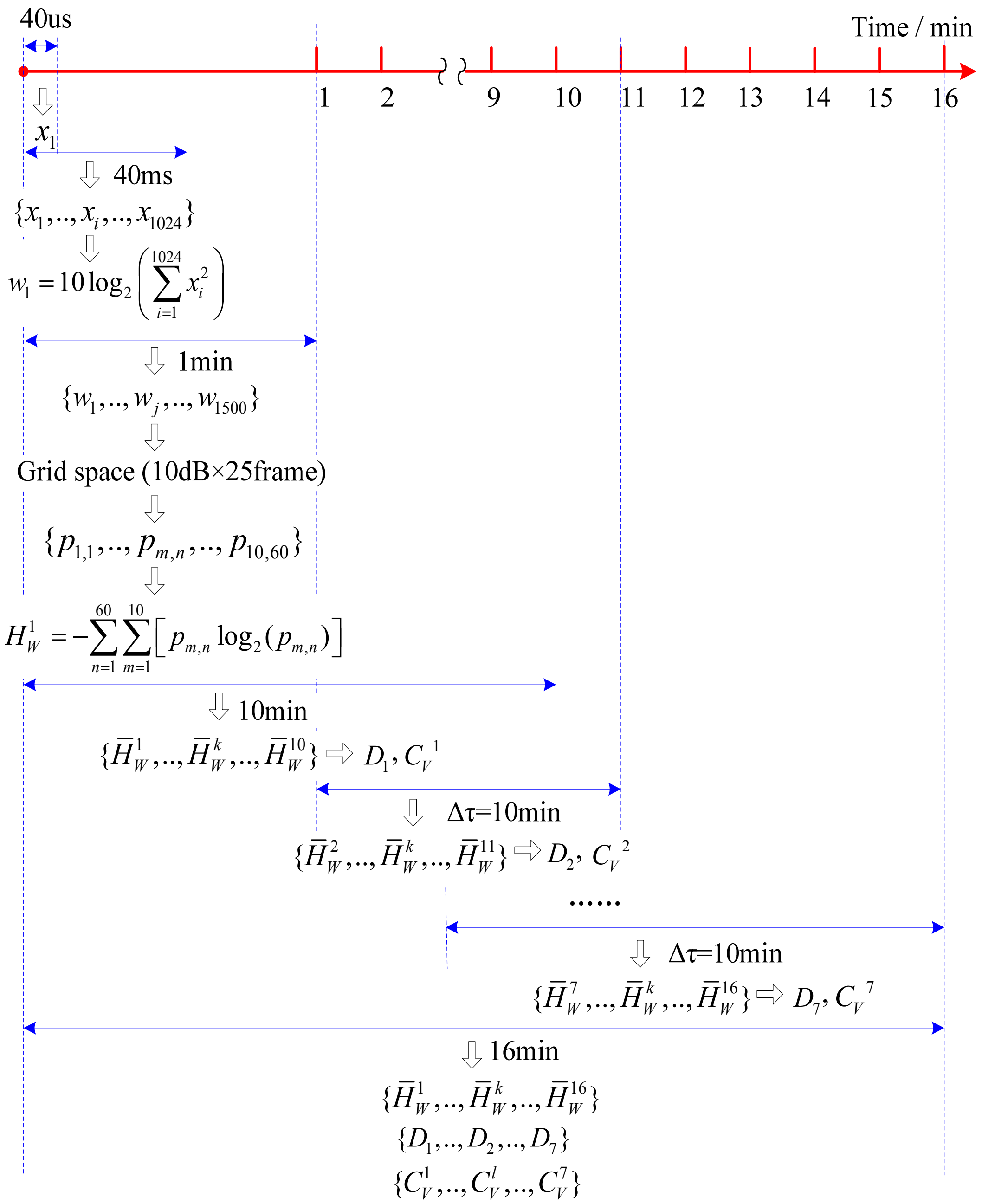

Fig. 6. Process to extracting $\overline{H}_W^k$, D_l and C_V^l.

4.2. Vibration Source Identification Result

We still use those vibration signals monitored by the OFVWS from some oil pipelines of the China Petroleum Pipeline Corporation for extracting their $\overline{H}_W^k$, D_l and C_V^l. The results are as shown in Figs. 7-9. We use a logarithmic y-axis in Fig. 9 in order to show the difference clearly.

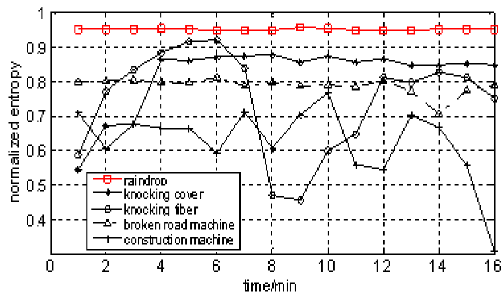

Fig. 7. Extracting result of $\overline{H}_W^k$.

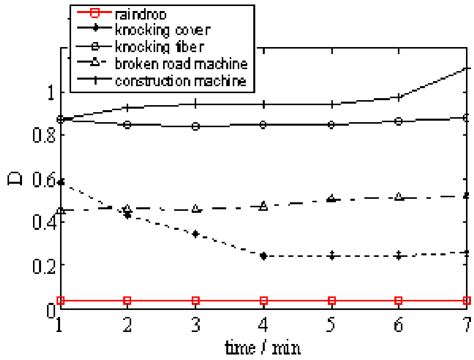

Fig. 8. Extracting result of D_l .

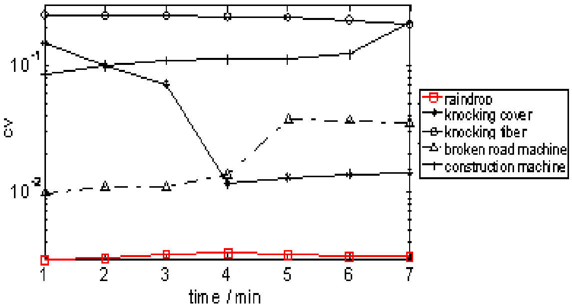

Fig. 9. Extracting result of C_V^l .

Let D_0=0.1 and C_{V0}=0.003. From Figs. 7-9, we can observe that: the priori known raindrop vibration signal satisfies criterion very well, hence the harmless raindrop vibration source can be identified and distinguished from other vibration sources evidently. In addition, Fig. 8 shows the feature of the stability of energy information entropy for raindrop vibration signals very well. Therefore, this identification approach based on the energy information entropy and its variation coefficient can help to improve the working reliability of the OFVMS by reducing the probability of false alarm.

5. Conclusions

In order to improve the working reliability of the OFVWS, the key way is to develop an effective approach to identifying harmless vibration signals and to reduce the probability of false alarm. In this paper, an approach based on energy information entropy was presented to identify raindrop vibration signal detected by the OFVWS. This approach is able to extract two obvious features of raindrop vibration signal, uniform signal energy and stable energy probability distribution, by using the normalized energy information entropy of vibration signal ($\overline{H}_W^k$), the average distance (D_l) and the variation coefficient (C_V^l). Combined with their thresholds, the harmless raindrop vibration signal can be identified from the other detected signals finally.

In order to investigate the performance of the presented approach, field data were used. The analysis results show that: the obvious features of raindrop signal can be extracted very well by calculating $\overline{H}_W^k$, D_l and C_V^l , hence the raindrop vibration source can be distinguished from the other vibration sources evidently.

This presented approach based on energy information entropy can identify the harmless raindrop vibration source accurately and help to improve its working reliability by reducing this probability of false alarm.

References

[1]. Y. R. Garcia, J. M. Corres, J. Goicoechea, Vibration detection using optical fiber sensors, *Journal of Sensors*, Article ID 936487, 2010, 12 pages.

[2]. G. Murtaza, S. L. Jones, J. M. Senior, N. Haigh, Loss behavior of single-mode optical fiber microbend sensors, *Fiber and Integrated Optics*, Vol. 20, Issue 1, 2001, pp. 53-58.

[3]. N. K. Pandey, B. C. Yadav, Embedded fibre optic microbend sensor for measurement of high pressure and crack detection, *Sensors and Actuators A*, Vol. 128, Issue 1, 2006, pp. 33-36.

[4]. H. Feng, Y. An, S. J. Jin, Z. M. Zeng, Desensitization Elimination in Pipeline Leakage Detection and Pre-warning System Based on the Modeling using Jones Matrix, in *Proceedings of the IEEE Sensors Applications Symposium* (*SAS*), 2010, pp. 101-104.

[5]. S. Binu, V. P. M. Pillai, N. Chandrasekaran, Fibre optic displacement sensor for the measurement of amplitude and frequency of vibration, *Optics and Laser Technology*, Vol. 39, Issue 8, 2007, pp. 1537-1543.

[6]. G. Wild, S. Hinckley, Acousto-ultrasonic optical fiber sensors: overview and state-of-the-art, *IEEE Sensors Journal,* Vol. 8, Issue 7, 2008, pp. 1184-1193.

[7]. B. Culshaw, Optical fiber sensor technologies: opportunities and-perhaps-pitfalls, *Journal of Lightwave Technology*, Vol. 22, Issue 1, 2004, pp. 39-50.

[8]. Y. Zhou, S. J. Jin, Y. C. Zhang, Distributed optical fiber sensing technology for pipeline leakage detection and location, *Acta Petrolei Sinica*, Vol. 27, Issue 2, 2006, pp. 121-124.

[9]. S. Tarr, G. Leach, The dependence of detection system performance on fence construction and detector location, in *Proceedings of the International Carnahan Conference on Security Technology*, Alexandria, VA, USA, 12-14 Oct, 1998.

[10]. S. S. Mahmoud, J. Katsifolis, Performance Investigation of Real-time Fiber Optic Perimeter Intrusion Detection Systems Using Event Classification. Security Technology (ICCST), in *Proceedings of IEEE International Carnahan Conference on Security Technology*, San Jose, California, USA, 5-8 October, 2010.

[11]. J. Vries, A low cost fence impact classification system with neural networks, in *Proceedings of IEEE Africon*, Vol. 2, 2004, pp. 131-136.

[12]. Z. G. Qu, S. J. Jin, Y. Zhou, Study on the distributed optical fiber pipeline leakage pre-warning system and the method of signal analysis, in *Proceedings of the 6th International Pipeline Conference*, Calgary, Canada, ASME, 25-29 September, 2006.

[13]. Z. G. Qu S. J. Jin, Z. M. Feng, Multi-scale chaotic characteristic analysis of detection signals in pipeline pre-warning system based on empirical mode decomposition, *ACTA Petrolei Sinica*, Vol. 29, Issue 2, 2008, pp. 313-316.

[14]. J. C. Zhang, Z. M. Zeng, F. Hao, S. J. Jin,. A recognition method of petroleum pipeline safety-detection events using the largest Lyapunov exponent and wavelet threshold de-noising, in *Proceedings of International Conference on Electronic Measurement & Instruments*, Beijing, China, 16-19 August, 2009.

[15]. Z. G. Qu, H. Feng, S. J. Jin, An SVM-Based recognition method for safety monitoring signals of oil and gas pipeline, *Journal of Tianjin University*, Vol. 42, Issue 5, 2009, pp. 465-470.

[16]. Z. M. Kand, G. L. Zhan, P. Xie, Implementation of an automation focusing algorithm based on spatial high frequency energy and entropy, *Acta Electronica Sinica*, Vol. 31, Issue 4, 2003, pp. 552-555.