ICA 2013 Montreal
Montreal, Canada
2 - 7 June 2013

Signal Processing in Acoustics
Session 1pSPb: Acoustic Feature Extraction and Characterization

1pSPb5. Abnormal events recognition and classification for pipeline monitoring systems based on vibration analysis and artificial neural networks

Bin Chen, Xiaobin Cheng*, Zhaoli Yan and Jun Yang

*Corresponding author's address: Institute of Acoustics, CAS, Beijing, 100190, Beijing, China, xb_cheng@mail.ioa.ac.cn

Pipelines become the principal means of oil and gas transportation. The leakage usually takes place due to some natural or artificial damages and causes loss of life and properties. Now a pre-warning system based on distributed optical fiber sensor has been proposed and deployed in China. Now, its following key problem is how to recognize and classify damage activities along with pipeline, such as ramming, rotor working, manual digging, well knocking, and mechanical execution. This paper involves in-depth study on recognition method for this system. Firstly, original vibration signal is pre-processed and segmented according to energy threshold and sliding window. Through statistical and short-time Fourier transform (STFT) analysis in time and frequency domain, energy ratios and frequency centroid are extracted as feature vectors, which can describe and distinguish distribution characteristics of each vibration event effectively. At classification, event set is divided firstly into discrete and continuous events with kurtosis, which can decrease classified event dimension and improve recognition accuracy. Then BP artificial neural network is applied to identify damage and non-threatening events. Experiment results show that proposed algorithm can differentiate discrete events with accuracy rate of 99%, while continuous events with 97.5%.

Published by the Acoustical Society of America through the American Institute of Physics
INTRODUCTION

Pipelines have become principal means of oil and gas transportation. However, pipeline leakage takes place due to some natural or artificial damages, which may cause loss of life and properties along with environmental pollution. Scientific workers and engineers investigate and develop several approaches for leakage monitoring, such as acoustic method, pressure gradient method, pressure point analysis, negative pressure method, and mass balance (Brunner and Barbezat, 2006; Li Han, 2009). Above methods have some common shortcomings. They can only detect leakage after enough accumulative total amounts, too late for prediction, and can’t tell which kind of activity causes. Another problem is poor ability of leakage source location.

Now, more and more researchers try to develop a pre-warning system that can detect damage activities as soon as it begins to drill hole or excavate soil just before damage occurs (Loth J.L, 2004; Zhou Y, 2005). Wang (2004) developed an acoustic detecting system being able to discriminate background noise and hammering signals. But it can only differentiate vibration signals with a limited distance of 2.4km. Recently, distributed fiber sensing system is regarded as an important direction to detect vibration events around pipeline. Wang (2008) proposed a general long-distance monitoring system with more than 50km. Its hardware has been accomplished and deployed. Then Zhang (2009) studied the chaotic character of petroleum pipeline detection signals and gave a recognition method for detection events with largest Lyapunov exponent and wavelet threshold de-noising.

Because long-distance oil pipeline may go through a variety of different environments, such as railways, rivers, roads, mountains and farmland, the interested vibration signal will be covered in many kinds of background noise. As we know, how to recognize and classify abnormal events with sensing vibration signals has not been solved well. Therefore, this paper involves in-depth study on it. The rest of the paper is organized as follows: Section 2 reviews the architecture of fiber sensing system. Section 3 introduces novel algorithm in detail. Then experimental example is given to show its efficiency in Section 4. Finally, a clear conclusion is drawn.

ARCHITECTURE OF THE PIPELINE MONITORING SYSTEM

The distributed pipeline sensing system is based on principle of Mach-Zehnder optical fiber interferometer. An optical cable is buried along pipeline to detect vibration signals, in which three single optical fibers L1, L2 and L3 are used as distributed vibration sensor, as shown in figure 1. Two fibers L1 and L2 are sensing, while the third one L3 is used to transport. The laser propagates along the fiber until it meets coupler 1 and then divided into two beams. They propagate along sensing and reference fiber respectively, and will be combined into interference signals at coupler 2. After that, interference signal is transported to photodiode though L3 and then transformed into electric signals. After amplifying, filtering and A/D converter, the electric signals are transported into computer for further processing.

When cable is affected by a vibration event along pipeline, it will generate stress and strain on optical fibers in cable. Thus two beams of coherent light waves propagating in L1 and L2 have changing phase and interference lights. Through photoelectric detectors, the light intensity signals are transformed into electric current signals, which is the function of modulated phase. According to the changes of interference optical signals, the system could detect vibration events along pipelines.

![FIGURE 1. The structure of system](image-url)
RECOGNITION ALGORITHM WITH VIBRATION ANALYSIS AND NEURAL NETWORKS

Data Preprocessing and Fragments Segmentation

Collected vibration signals usually contain a lot of high and low frequency noises, including geological vibration and AC frequency noise. In our prior knowledge, detected vibration event can be heard with human ears, while sampling frequency of system is high. In the first step, it is down-sampled to reduce calculation and background noise.

To satisfy real-time requirement of monitoring system, vibration signal should be separated into independent fragments. Through statistical analysis of many event samples, we set a reasonable window width of fragment according to maximum duration of all discrete events, such as ramming, manual digging and well knocking. The principle is that it can locate every pulse signal completely in a continuous vibration signal and obtain its stable spectrum characteristics. Then compute energy within a small window in time domain and justify whether it goes beyond on an energy threshold. To find and locate an event accurately, we apply with a small sliding window to process continuous vibration signal. For a ramming event with 10 seconds, its segmentation result with small sliding window 8 is shown in figure 2. We can see that every pulse in ramming vibration signal could be located accurately.

Feature Extraction

Feature extraction is the process of capturing complex structure in a signal using as few features as possible. When we design classifying algorithm, one main challenge is to find most separating features for all events. Through hearing lots of vibration signals of different events, we found that they can be accurately distinguished with human ears. That is to say, they should have different characteristics in time and frequency domain. Therefore, we apply with Short Time Fourier Transform (STFT) technology to analyze vibration signals. The STFT is defined as

\[ X_{\text{STFT}} = \sum_{m=-\infty}^{\infty} x[n-m]w[m]e^{-j\frac{2\pi nm}{N}} \]  

Where \( w(\cdot) \) is a window function, such as hamming or hanning window. Figure 3 demonstrates on some events’ STFT results in 4s vibration signal.
We can find that: (a) All events usually concentrated their energy in 50Hz~1000Hz. (b) They have their own obvious distribution characteristics in time and frequency domain. For example, the energy of train running event concentrates at frequency bands [100Hz, 200Hz], while well knocking event concentrates at high frequency bands. Therefore, the energy ratios in different frequency bands are calculated and extracted as features to distinguish events. In addition, the bandwidth should be neither wide nor narrow. If too narrow, the feature’s uncertainty or stability becomes worse. Otherwise, it will have no separating capacity.

The power spectrum reflects frequency component and energy of each frequency in vibration signal. The centroid of power spectrum defines true mean frequency in the signal, which will change along with different vibration events. To a vibration signal sequence $x(n)$, its centroid frequency is defined as:

$$f_c = \frac{\int wS(w)dw}{\int S(w)dw} = \frac{\sum_{k=0}^{(N-1)/2} \frac{2\pi k}{N} P_{\text{seq}}(k)}{\sum_{k=0}^{(N-1)/2} P_{\text{seq}}(k)}$$

Where $f_s$ is sampling frequency, $S(w)$ is power spectrum of signal. Therefore, the position of centroid frequency is $f_c = f_s / N$, $P_{\text{seq}}(k)$ are power spectrum of signal. Therefore, the position of centroid frequency

$\hat{f}_c = \frac{f_s}{N}$.

### Events Recognition and Classification

Above extracted features are used as input vector of classifiers. Previous researchers generally process whole events without distinguishing continuous and discrete events. In fact, the width of fragment has a great influence on recognition accuracy of continuous events because it only considers maximum duration of pulse signal during data preprocessing. Furthermore, it will increase feature uncertainty of continuous events. It’s necessary to make a difference between two kinds of events. The kurtosis describes impact characteristics in vibration signal and can be used to divide event sets into continuous and discrete events. It is defined as follows:

$$K = \frac{1}{N} \sum_{i=1}^{N} \left( \frac{x_i - \bar{x}}{\sigma} \right)^4$$

Where $\sigma$ is standard deviation of vibration signal $x(n)$.

The neural network has ability of strong nonlinear mapping, self-learning, parallel computation, and excellent fault-tolerance performance. It can handle large dimensionality and non-linear characteristics of pipeline leakage recognition problems. Now, there are many types of neural models, such as feed-forward, feedback and self-
organizing pattern. In this paper, we apply with back propagation neural network (BPNN) to process continuous and discrete events and finish final recognition. Figure 3 gives BPNN’s structure, which is composed by input layer, hidden layer and output layer.

\[ n_i = \sqrt{p + q + \delta} \]  

(4)

FIGURE 3. The structure of BP neural network

According to BPNN’s basic principle, the number of output neurons \( p \) is equal to the types of events. For example, discrete event should be 4, and its objective vector can denote by \( T = [1 0 0 0; 0 1 0 0; 0 0 1 0; 0 0 0 1] \). While input neurons \( q \) depend on total number of energy ratios and spectrum centroid. We first ensure the range of neurons in hidden layer according to following empirical formula.

\[ \|w\| \leq \frac{1}{\sqrt{q}} \]

Then optimal neurons are chosen according to minimum training time and highest prediction accuracy.

In order to speed up convergence, we would like to increase learning rate. However, the algorithm will become unstable and oscillate back and forth when learning rate is rapid. To the drawbacks of back propagation, an improved heuristic modification is introduced, which adds momentum into change of parameter. The modified equations are as follows:

\[
\begin{align*}
\Delta W^d(k) &= \gamma \Delta W^d(k-1) - (1-\gamma)w^d(d^d)^T \\
\Delta b^d(k) &= \gamma \Delta b^d(k-1) - (1-\gamma)b^d
\end{align*}
\]

(5)

where \( \gamma \) is the momentum coefficient and set to 0.95, \( w^d(k) \), \( b^d(k) \) and \( s^d \) is weight vector, bias vector, sensitivity function in \( d^d \) layer.

EXPERIMENTAL ANALYSIS

The experimental data are collected from China National Petroleum Corporation, located in Langfang, Hebei Province. They have deployed long-distance optical fiber on several trunk pipelines in China. The fibers are buried directly in the soil with different depths from 0.5m to 2m. We collect eight kinds of vibration, including ramming, rotor working, manual digging, well knocking, mechanical execution, pipe protection, cable burying and train running. The first five are damage activities, while the other three are non-threatening activities. According to the principle in feature extraction, we divide 50Hz–1000Hz bandwidth into equal bands with 50Hz. Therefore the feature vector contains 19 energy ratios and one spectrum centroid. The relative parameters are shown in Table 1.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
</table>

TABLE 1. Recognition results with different methods
Choose 40 fragments from each type of event randomly, the kurtosis distribution is shown in Figure 4. We can see that the value of discrete events, such as manual digging, ramming, well knocking, cable burying, is much greater than other continuous events.

According to Eq.4, hidden neurons belong to interval [6, 15]. It is chosen as 9 through optimal trial, and the structure of BPNN is determined as 20→9→4 (input nodes, hidden neurons and out nodes). We select 100 training samples and 50 testing samples randomly from each event. The Experimental results with different methods are shown in Table 2. We find that recognition rate of both continuous and discrete events can reach above 97.5%, much better than the results of BPNN with all events.

**TABLE 2. Recognition results with different methods**

<table>
<thead>
<tr>
<th>Methods</th>
<th>Accuracy(%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>BPNN with all events</td>
<td>79.25%(317/400)</td>
</tr>
<tr>
<td>BPNN with continuous events</td>
<td>97.5%(195/200)</td>
</tr>
<tr>
<td>BPNN with discrete events</td>
<td>99(198/200)</td>
</tr>
</tbody>
</table>

**CONCLUSION**

A recognition and classification method with vibration analysis and BPNN is proposed for distributed optical fiber sensing system. In algorithm, event set is divided into discrete and continuous kinds which can improve recognition accuracy greatly. Through STFT analysis, vibration signal is segmented reasonably with energy threshold and sliding window. Extracted energy ratios and frequency centroid describe different characteristics of each event effectively. BPNN classifier is well designed with optimal hidden neurons and heuristic modification method. Experiment results
show that proposed algorithm can differentiate discrete events with accuracy rate of 99%, while continuous events with 97.5%.

In this paper, five types of damage activities and three kinds of non-threatening activities were classified accurately. The future work will improve the algorithm and identify other kinds of events, in particular, mixture of several kinds of events.

REFERENCES


