Application of time-frequency image feature extraction method based on gray level co-occurrence matrix in coal mine pipeline leakage detection

Wenbei Han1, Hongliang Zhao*, Ziwei Zhao, Fengshou Gu, Dong Zhen

1College of Electrical Engineering and Automation, Shandong University of Science and Technology, Qingdao, Shandong, 266590, China
*zhl6401p@126.com

Abstract: The underground mining environment of coal mine is complex. Once the water supply or gas supply pipes leak, the location and time of leakage are unpredictable. If the leakage can not be found in time, it will seriously threaten the life safety of underground workers. Therefore, it is very necessary to automatically detect the pipeline leakage. In order to solve the problem of automatic detection of coal mine pipeline leakage, this paper proposes an image processing method based on gray level co-occurrence matrix to extract the features of time-frequency image of vibration signal. Firstly, the data in a relatively short time is divided into one frame to reduce the amount of calculation. Secondly, each frame of signal is processed by SPWVD to get the time-frequency image. Then, the time-frequency image after time-frequency analysis is transformed into gray-scale image, and the gray-scale co-occurrence matrix (GLCM) of the image is extracted. Finally, the energy, contrast and correlation of the co-occurrence matrix are extracted and input to SVM for learning and training. Through the design and build of the experimental pipeline to test the algorithm proposed in this paper, the detection result of SVM is 96.67%, which shows that this method can effectively detect the pipeline leakage.

1. Introduction
Leakage of underground pipelines in coal mines has always been a key concern during the mining process. The working conditions under the coal mine are very complicated, and the pipelines will not be easily repaired after being laid. These pipelines work in a humid environment under the mine for a long time, and it is very susceptible to corrosion and leakage [1]. Pipeline leakage is accidental, so it is impossible to artificially predict the location and time of the leakage [2]. If the leakage cannot be found in time, on the one hand, it will cause a lot of waste of resources and increase the cost of mining; on the other hand, downhole pressurized air and water supply pipeline is closely related to the life safety of underground workers, so pipeline leakage will endanger the life safety of these workers [3-4]. The traditional method relies on manual inspection of the pipeline, but this method takes a lot of time and wastes human and financial resources, so it is of great significance to automatically detect pipeline leakage.

With the development of technology, various methods have been proposed for pipeline leak detection. Some scholars have studied the external detection methods of pipeline leakage. Acoustic emission method [23] is widely used in engineering. Li Shuaiyong et al. [6] proposed an adaptive leak detection and localization method for natural gas pipelines using acoustic emission sensors. Which collects acoustic wave signals by AE sensors, and the acoustic signal carried information on the source...
of a gas leak can help people to detect the occurrence and location of a gas leak. However, acoustic emission is very sensitive to random environmental noise and is very susceptible to noise interference. The accelerometer measurement method [7] overcomes this shortcoming. El-Zahab et al. [8] proposed a model of a real-time monitoring system. This model places a wireless accelerometer in a pipeline network through a connected valve, and inputs the collected signals into the SVM for analysis, which can accurately identify whether a water supply pipeline leakage has occurred. Martini et al. [9] studied the leakage detection method based on the inherent characteristics of the measured signal rather than the relative amplitude. By using two accelerometers and a hydrophone to measure the leakage, and analyzing the autocorrelation function of the measurement signals, the possibility of detecting water leakage in small diameter plastic pipes was evaluated. Tanimola et al. [11] studied the optical fiber method [24], taking the LNG and LPG pipeline leakage detection device as an example, expounded the principle of leak detection and third-party intruder detection of optical fiber distributed temperature sensing, and the results of the fiber-optic distributed acoustic sensing intruder monitoring case study, so as to improve pipeline protection, increase pipeline transportation rates and strengthen environmental protection.

There are also some scholars who have studied the internal detection methods of pipeline leakage. The negative pressure wave method [12] [13] has been favored by many scholars because of its fast response speed, low cost, and high accuracy of locating leaks in pipelines. Chen Q et al. [14] proposed a numerical method for calculating the propagation velocity of pressure waves in a liquid pipeline. On this basis, the self-made pipeline leak detection experimental platform was used to measure the propagation speed of NPWS experimentally, which verified the feasibility of the proposed method. The pressure point analysis method is also a type of internal leak detection method, which measures the statistical characteristics of pressure at different points along the pipeline. Leaks are determined by comparing measured values with previously measured operational statistical trends [15]. Afifi et al. [26] proposed a mathematical derivation for calculating the pressure before leakage and the pressure at the leak point. The pressure at the point of leakage has a great relationship with the mass flow of the substance, so the derivation of accidental leakage is also proposed. The results show that pipeline leakage can be detected based on the derived pressure comparison. Various digital signal processing methods have been adopted in the field of pipeline research, such as wavelet transform [17], impedance method [18], cross correlation [19], and Haar wavelet transform [20]. Since two-dimensional signals can highlight some of the weaker features of the signals than one-dimensional signals, leak detection methods based on two-dimensional images are also continuously developed. Kousiopoulos [21] et al. used time-frequency analysis to locate the leaking cracks in gas pipelines, determined the time difference through the time-frequency diagram of the STFT transform of the waveforms measured by two sensors, and then determined the crack location based on the speed of sound. Li Hongwei [22] and others proposed a method for leakage detection using improved wavelet denoising and short-time Fourier transform, which can be used to monitor pipeline leakage in real time.

In order to obtain the time-frequency graph of the signal, time-frequency analysis of the signal is required. There are many methods for signal time-frequency analysis, including short-time Fourier transform [5], wavelet transform [10], Wigner-Ville distribution [25], and so on. However, these methods all have some shortcomings. Short-time Fourier transform requires short time windows when processing high-frequency information and long time windows when processing low-frequency information. Therefore, it is difficult to choose a suitable window length when processing non-stationary signals. The wavelet transform theory is limited by the Basic Uncertainty Principle, so it is difficult to choose a suitable wavelet scale. The Wigner-Ville distribution can be regarded as the distribution of the energy of the signal in the time and frequency domains. For the multi-component signal Wigner-Ville distribution, there will be significant oscillating cross terms, and the time-frequency characteristics of the signal cannot be clearly obtained. Based on the Wigner-Ville distribution, SPWVD adds a kernel function to achieve the function of suppressing the cross terms [16].

This paper selects SPWVD to convert one-dimensional time-domain signals into two-dimensional spatial images, then uses GLCM for feature extraction, and finally uses SVM support vector machine
for classification, which provides a new method for pipeline leakage information processing. This article introduces the overall algorithm implementation process and algorithm principle, and sets up a test platform in the laboratory. The superiority of this method in information feature extraction and leakage judgment is verified by experiments.

2. Overall algorithm structure

This paper proposes a pipeline leak detection method based on the time-frequency images and GLCM. This method uses SPWVD and SVM to process and classify pipeline vibration signals. First, the vibration signal \( x(n), n \in \{1, ..., R\} \) of the pipeline is collected by the sensor, and the signal \( x(n) \) is processed in frames. The \( N \) sampling points are aggregated into an observation unit to form a frame. In order to avoid excessive changes in two adjacent frames, an overlapping area is set between the two adjacent frames, and the overlapping area includes \( N/2 \) sampling points. SPWVD processing is performed on the signal \( s(n) \) obtained after framing. The calculation formula is shown in equation (1):

\[
SPW_{n,k}(n,k) = 2 \sum_{m=-F+1}^{F-1} [h(m)]^2 \cdot \sum_{p=-M+1}^{M-1} g(p)x(n+p+m) \cdot x'((n+p-m)e^{-j2\pi nk/F})
\]

(1)

Where \( n \) and \( k \) are discrete time and frequency indexes, \( h(m) \) is a frequency smoothing symmetry norm window with length \( (2F-1) \), and \( g(p) \) is a time smooth symmetry normative window with length \( (2M-1) \).

Then, the time-frequency image of the signal is obtained after SPWVD processing, and a grayscale image \( I \) with a grayscale level \( G \) is obtained after the grayscale processing. The GLCM is used to extract the features of the image \( I \). An image can be represented as a mapping from its horizontal spatial domain \( X \) and vertical spatial domain \( Y \) to a grayscale domain \( U \), that is, \( f: X \times Y \rightarrow U \). In the pixel matrix point of image \( I \), select any pixel point \((x, y)\) whose gray value is \( i \), and determine the direction \( \theta \) and distance \( d \) of the GLCM to obtain another pixel point with a gray value of \( j \) \((x+a, y+b)\), and record the gray value of this pair of points as \((i, j)\). Make \((x, y)\) traverse the entire image, and according to the number of gray levels \( G \), we can know that \((i, j)\) can reach at most \( G^2 \) kinds combination. Therefore, the GLCM of image \( I \) is a square matrix of \( G \times G \), and each element coordinate \((i, j)\) of the square matrix represents the number of times a corresponding gray level pair \((i, j)\) appears in the image. The mathematical expression is:

\[
P(i, j, d, \theta) = \{(x, y),(x+a, y+b)|f(x, y) = i; f(x+a, y+b) = j\}
\]

(2)

Generally, the feature parameters of the GLCM are extracted for image recognition. Haralick et al. have defined the second-order statistics of 14 types of GLCMs. This paper selects three characteristic parameters of energy, contrast and correlation.

Energy:

\[
ASM = \sum_{i=1}^{G} \sum_{j=1}^{G} P^2(i, j, d, \theta)
\]

(3)

Contrast:

\[
CON = \sum_{i=1}^{G} \sum_{j=1}^{G} [(i-j)^2 \cdot P^2(i, j, d, \theta)]
\]

(4)

Correlation:

\[
COR = \sum_{i=1}^{G} \sum_{j=1}^{G} [i \times j \times P(i, j, d, \theta) - u_1 \times u_2]/(d_1 \times d_2)
\]

(5)

\[
u_1 = \sum_{j=1}^{G} \sum_{i=1}^{G} P(i, j, d, \theta)
\]

\[
u_2 = \sum_{i=1}^{G} \sum_{j=1}^{G} P(i, j, d, \theta)
\]

\[
u_3 = \sum_{i=1}^{G} (i-u_1)^2 \sum_{j=1}^{G} P(i, j, d, \theta)
\]

\[
u_4 = \sum_{i=1}^{G} (j-u_2)^2 \sum_{j=1}^{G} P(i, j, d, \theta)
\]
Finally, select L groups of samples and extract the feature vectors \( t_1, \ldots, t_L \in \mathbb{R}^d \), \( r_i \in \{-1, 1\} \) through the above characteristic parameters, and then input them to the SVM for training and classification. The decision function of SVM is shown in equation (6):

\[
\max_{\lambda} \sum_{i=1}^{L} \lambda_i - \frac{1}{2} \sum_{i=1}^{L} \sum_{j=1}^{L} \alpha_i \alpha_j r_i r_j t_i t_j
\]

s.t. \( \sum_{i=1}^{L} \lambda_i r_i = 0 \quad 0 \leq \lambda_i \leq C \quad 1 \leq i \leq L \)  \hspace{1cm} (6)

Where \( \lambda_i \) is the Lagrangian multiplier, \( L \) is the number of samples, and \( C > 0 \) is the regularization constant.

In summary, the flowchart of the proposed algorithm is shown in Figure 1.

![flowchart](image)

Figure 1. Overall flow chart of signal algorithm.

### 3. Experimental pipeline and test platform

#### 3.1 Experimental pipeline

The pipeline was constructed of PP-R pipes, with a total of 6 pipe sections. A switching valve and an air inlet were placed in the pipeline. The standard for pipe sections was 32mm outside diameter and 4.4mm wall thickness. Among them, pipe section 1, pipe section 2, pipe section 3, pipe section 4, pipe section 5, and pipe section 6 were 65.5 cm, 90 cm, 76 cm, 126 cm, 115 cm, and 123 cm respectively. In the figure, P1 was the on-off valve, which was used to simulate the leakage state of the pipeline. S1 and S2 were MEMS acceleration sensors, which were respectively installed on both sides of the leakage valve, and were used to collect vibration signals generated when the pipeline leaked.

![pipeline](image)

Figure 2. Experimental pipeline structure and sensor arrangement.

#### 3.2 Test system

The experimental system was mainly composed of pipelines, air compressors, two MEMS acceleration
sensors, PXI Express system and virtual instrument development environment. The selected MEMS acceleration sensor model was ADXL001 ± 70g, the chassis model was NI PXIe-1071, the controller model was NI PXIe-8820, and the peripheral module selected the data acquisition card of model NI PXIe-4499 for multi-channel pipeline leakage signal collection. The role of the air compressor was to provide air to the pipeline, so that the pressure in the pipeline can reach and maintain a preset value.

4. Analysis of experimental data

Used the pipeline shown in Figure 2 to conduct experiments. The valve P in the pipe section 5 was controlled to simulate whether the pipeline was leaking. The acceleration sensor 1 was 26.5 cm away from the valve, and the acceleration sensor 2 was 33.5 cm away from the valve. The compressor was used for gas filling, and the rated air pressure was set to 0.8 MPa. When the compressor stopped filling, that is, when the pressure in the pipe reached 0.8 MPa, the acceleration sensor collected a set of data. Turned on switch P1 to simulate a leak in the pipeline. At the moment, the acceleration sensor collected a set of data. The data collected before and after the acceleration sensor 1 and the accelerometer 2 leak are shown in Figure 3.

![Figure 3. Time domain diagram of vibration signal.](image)

It can be seen from Figure 3 that the leakage signal is similar to the normal signal waveform. The amplitude of the signal collected by sensor 1 is greater than the amplitude of the signal collected by sensor 2, so it can be known that the size of the data collected by the sensor is related to the distance from the sensor to the leak point. When the leak point is far away from the sensor, it is difficult to distinguish the leak signal from the non-leak signal from the time domain.

The signal was processed by the method mentioned in this paper. First, the signal collected by the sensor 1 was subjected to frame processing, and the data length of each frame was selected to be 500 sampling points, and the overlapping area contained 200 sampling points. The sampling frequency of the pipeline vibration signal in this study was 10KHz, so the corresponding time length was 500/10000 = 0.05s. Took one frame for the leak signal and one for the normal signal, and did SPWVD processing. The time-frequency image of the signal is shown in Figure 4.

![Figure 4. Time frequency diagram of vibration signal.](image)

It can be seen from Figure 4 that the time-frequency diagrams of the leakage signal and the normal signal are obviously different, and it is necessary to use image processing method to perform feature extraction on the time-frequency image. This paper chose the GLCM method. The GLCMs obtained at different angles is different. Since the main texture direction of the time-frequency image was 0° direction, the GLCM with a distance of 1 in the 0° direction of the image was obtained. The calculated GLCMs of the two images is shown in Table 1 and Table 2.
Table 1. Gray level co-occurrence matrix of normal signal.

|       | 23177 | 11953 | 237  | 0     | 0     | 0     | 0     |
|-------|-------|-------|------|-------|-------|-------|-------|
| 11712 | 80790 | 23268 | 239  | 0     | 0     | 0     | 0     |
| 250   | 22119 | 86522 | 21505| 0     | 0     | 0     | 0     |
| 0     | 346   | 20535 | 71226| 2970  | 451   | 0     | 0     |
| 0     | 0     | 0     | 2825 | 2051  | 1271  | 57    | 0     |
| 0     | 0     | 0     | 5    | 82    | 393   | 364   | 63    |
| 0     | 0     | 0     | 0    | 0     | 17    | 70    | 67    |

Table 2. Gray level co-occurrence matrix of leakage signal.

|       | 238848 | 2682  | 0     | 0     | 0     | 0     | 0     |
|-------|--------|-------|-------|-------|-------|-------|-------|
| 2457  | 63952  | 1349  | 0     | 0     | 0     | 0     | 0     |
| 0     | 1205   | 35754 | 988   | 0     | 0     | 0     | 0     |
| 0     | 0     | 1153  | 31027 | 300   | 0     | 0     | 0     |
| 0     | 0     | 0     | 485   | 5847  | 150   | 0     | 0     |
| 0     | 0     | 0     | 0     | 283   | 2435  | 0     | 0     |
| 0     | 0     | 0     | 0     | 0     | 75    | 474   | 0     |
| 0     | 0     | 0     | 0     | 0     | 0     | 50    | 183   |

The comparison between Table 1 and Table 2 shows that the non-zero values in the GLCMs of the leakage signal are more concentratedly distributed around the diagonal, and the signal texture is clear. The element values in the feature matrix of the normal signal are relatively scattered, indicating that the signal has no uniform texture. Calculate the characteristic parameters of the two GLCMs, as shown in Table 3.

Table 3. Parameter table of gray level co-occurrence matrix.

|       | Contrast | Relevance | Energy |
|-------|----------|-----------|--------|
| Normal| 0.33     | 0.98      | 0.14   |
| Leak  | 0.03     | 0.84      | 0.42   |

Contrast reflects the sharpness of the image and the degree of texture grooves. The larger the value of the element far from the diagonal in the GLCM, the greater the contrast. The matrix in Table 1 has more elements farther away from the diagonal and has larger values, so the contrast of normal signals is greater. Correlation reflects the similarity of the spatial GLCM elements in the row or column direction. Therefore, the correlation value reflects the local gray level correlation in the image. When the matrix element values are uniformly equal, the correlation value will be large; on the contrary, if the matrix element values are greatly different, the correlation value will be small. The difference in element values in the matrix in Table 2 is larger, so the correlation obtained is smaller. The energy reflects the uniformity of the gray distribution of the image and the thickness of the texture. If all values of the co-occurrence matrix are equal, the energy value will be small; on the contrary, if some of the values are large and others are small, the energy value will be large. Because the element values of the matrix in Table 2 differ greatly, the energy of the leak signal is larger, indicating that the texture of the time-frequency graph of the leak signal is regular and more uniform.

This paper selected 100 frames of leaking signals and 100 frames of non-leaking signals, processed them as described above, and inputted the extracted feature values into the SVM for training. Another 120 groups of signals were selected for classification testing, and the classification result was 96.67%, as shown in the Figure 5. The experimental results show that the method proposed in this paper is reasonable in the field of pipeline leak diagnosis, and can accurately and timely determine whether a pipeline leakage occurs.
5. Conclusion

Image recognition is more and more widely used in various fields. This article took the pipeline leakage diagnosis as an example. The SPWVD distribution of the pipeline vibration signal was used to convert one-dimensional signals into two-dimensional time-frequency images. GLCM was used to extract image features, and the three characteristic parameters of energy, correlation, and contrast of the GLCM were obtained. These three parameters are significantly different from the normal state of the leak, which greatly improves the automatic leakage detection performance. Under the trend of intelligent development, using time-frequency domain images for fault diagnosis and detection undoubtedly has broad prospects.

References

[1] Arifin, B. M. S., Li, Z., Shah, S. L., Meyer, G. A., & Colin, A. (2018). A novel data-driven leak detection and localization algorithm using the Kantorovich distance. Computers & Chemical Engineering, 108, 300-313.
[2] Lukman, A. J. A. O., EMMANUEL, A., Chinonso, N., Mutiu, A., James, A., & Jonathan, K. (2018). An Anti-Theft Oil Pipeline Vandalism Detection: Embedded System Development. International Journal of Engineering Science and Application, 2(2), 55-64.
[3] Adegboye, M. A., Fung, W., & Karnik, A. (2019). Recent advances in pipeline monitoring and oil leakage detection technologies: principles and approaches. Sensors, 19(11).
[4] Xiao, R., Hu, Q., & Li, J. (2019). Leak detection of gas pipelines using acoustic signals based on wavelet transform and Support Vector Machine. Measurement, 146, 479-489.
[5] Hao, T., Xue, Y., Zheng, Z. (2019) Noise feature extraction based on short-time fractional Fourier transform. Journal of naval aeronautical engineering college, 34(03):273-276+309.
[6] Li, S., Wen, Y., Li, P., Yang, J., & Yang, L. (2012). Leak detection and location for gas pipelines using acoustic emission sensors. In 2012 IEEE International Ultrasonics Symposium. pp. 957-960.
[7] Karkulali, P., Mishra, H., Ukil, A., & Dauwels, J. (2016, October). Leak detection in gas distribution pipelines using acoustic impact monitoring. In IECO 2016-42nd Annual Conference of the IEEE Industrial Electronics Society. pp. 412-416.
[8] El-Zahab, S., Abdelkader, E. M., & Zayed, T. (2018). An accelerometer-based leak detection system. Mechanical Systems and Signal Processing, 108, 276-291.
[9] Martini, A., Rivola, A., & Troncossi, M. (2018). Autocorrelation Analysis of Vibro-Acoustic Signals Measured in a Test Field for Water Leak Detection. Applied Sciences, 8(12), 2450.
[10] Guan, X. (2019) Research on wavelet transform image processing technology. Journal of cangzhou normal university, 35(01):44-46+73.
[11] Tanimola, F., & Hill, D. (2009). Distributed fibre optic sensors for pipeline protection. Journal of Natural Gas Science and Engineering, 1(4-5), 134-143.
[12] Sang, Y., Zhang, J., Lu, X., & Fan, Y. (2006). Signal processing based on wavelet transform in pipeline leakage detection and location. In Sixth International Conference on Intelligent Systems Design and Applications. Vol. 2, pp. 734-739.

[13] Yu, Z., Jian, L., Zhoumo, Z., & Jin, S. (2009, August). A combined kalman filter—Discrete wavelet transform method for leakage detection of crude oil pipelines. In 2009 9th International Conference on Electronic Measurement & Instruments. pp. 3-1086.

[14] Chen, Q., Shen, G., Jiang, J., Diao, X., Wang, Z., Ni, L., & Dou, Z. (2018). Effect of rubber washers on leak location for assembled pressurized liquid pipeline based on negative pressure wave method. Process Safety and Environmental Protection, 119, 181-190.

[15] Adegbuyi, M. A., Fung, W. K., & Karnik, A. (2019). Recent advances in pipeline monitoring and oil leakage detection technologies: principles and approaches. Sensors, 19(11), 2548.

[16] Liu, F., Ye, F. (2007) Study on estimation method of SPWVD parameter of frequency hopping signal. Computers and information technology, 15(6): 28-30.

[17] Ocak, H. (2009). Automatic detection of epileptic seizures in EEG using discrete wavelet transform and approximate entropy. Expert Systems with Applications, 36(2), 2027-2036.

[18] Lay-Ekuakille, A., Vergallo, P., & Trotta, A. (2010). Impedance method for leak detection in zigzag pipelines. Measurement Science Review, 10(6), 209-213.

[19] Gao, Y., Liu, Y., Ma, Y., Cheng, X., & Yang, J. (2018). Application of the differentiation process into the correlation-based leak detection in urban pipeline networks. Mechanical Systems and Signal Processing, 112, 251-264.

[20] Peng, Z., Wang, J., & Han, X. (2011, August). A study of negative pressure wave method based on haar wavelet transform in ship piping leakage detection system. In 2011 IEEE 2nd International Conference on Computing, Control and Industrial Engineering. Vol. 2, pp. 111-113.

[21] Kouziopoulos, G. P., Papastavrou, G. N., Karagiorgos, N., Nikolaidis, S., & Porlidas, D. (2019). Pipeline Leak Detection in Noisy Environment. In 2019 8th International Conference on Modern Circuits and Systems Technologies (MOCAST). pp. 1-5.

[22] Li, H., Li, H., Pei, H., & Li, Z. (2019). Leakage detection of HVAC pipeline network based on pressure signal diagnosis. Building Simulation, 12(4), 1-12.

[23] Meng, L., Yuxing, L., Wuchang, W., & Juntao, F. (2012). Experimental study on leak detection and location for gas pipeline based on acoustic method. Journal of Loss Prevention in The Process Industries, 25(1), 90-102.

[24] Du, J., Wang, L., Cai, C., Yin, C., & Zhao, G. (2017). Study on distributed optical fiber heating pipeline network leak detection system. In 2017 IEEE 2nd Information Technology, Networking, Electronic and Automation Control Conference (ITNEC). pp. 137-140.

[25] Yang, H., Liu, Z., Li, L. (2018) Study on time-frequency characteristics of chaotic signals based on wigner-ville distribution. Modern navigation, 9(06): 447-450+454.

[26] Bin MdAkib, A., Bin Saad, N., & Asirvadam, V. (2011). Pressure point analysis for early detection system. In 2011 IEEE 7th International Colloquium on Signal Processing and its Applications. pp. 103-107.