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Leak Detection and Location Based on ISLMD and CNN in a Pipeline

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ABSTRACT The key to leak detection and location in water supply pipelines is signal denoising and feature extraction. First, in this paper, an improved spline-local mean decomposition (ISLMD) is proposed to eliminate noise interference. Based on the ISLMD decomposition of a signal, the cross-correlation function between the reference signal and the product functions component can be obtained. And then the PF component containing the leak information can be extracted reasonably. Compared with improved local mean decomposition, the ISLMD has higher accuracy in leak location. Second, an image recognition method using a convolutional neural network for leak detection is proposed, which can better address the problem that the features of different leak apertures or locations are highly similar to each other. The images from the conversion of the reconstructed signals are used as the input of the AlexNet model, which is capable of adaptive extraction of leak signal features. The trained AlexNet model can effectively detect different leak apertures. Finally, the signal time-delay between the upstream and downstream pressure transmitters caused by the leak and propagation of negative pressure wave is determined according to generalized cross-correlation analysis, and thereby, the leak location is obtained. The experimental results show that the proposed method is effective for leak detection and location.

INDEX TERMS Local mean decomposition, convolutional neural network, generalized cross-correlation, leak detection and location, fault detection.

I. INTRODUCTION

Water supply pipelines play a highly important role in the infrastructure of cities and factories. However, pipelines are susceptible to leak due to such factors as the environment, aging pipe, external forces, and corrosion [1]. Leaks not only cause waste of resources but also environmental pollution. Therefore, the research of pipeline leak detection and location has attracted increasing research attention, and a large number of solutions have been proposed [2]–[4]. For example, Zadkarami *et al.* [5] proposed the use of pressure and flow to construct a multilayer perceptual neural network for leak detection. Song and Li [6] proposed acoustic emission and artificial neural networks to detect leakage. In general, there are two categories of methods for detecting pipeline leakage, namely hardware-based and software-based, or externally-based and internally-based [3], [7]. In hardware-based approaches, special sensing devices are used to detect pipeline leakage. And the software-based methods rely on a variety of software programs, which have been effectively used for pipeline leakage. In addition, in some methods, both hardware and software are employed simultaneously. The software-based methods are more popular among researchers because of their relatively low cost, ease of maintenance, and deployment. The representative methods include digital signal processing, mass/volume balance, negative pressure wave (NPW), real-time transient modeling (RTTM), statistical technique, etc. Among all the solutions, the NPW method, which has the advantages of simple operation, high speed and accurate positioning, is widely used [8], [9].

When a leak occurs, the pressure declines quickly at the leak point due to the pressure difference between the inside and outside of the pipeline. The negative pressure is generated inside the pipe, propagating to the upstream and downstream. The upstream and downstream pressure sensors/transmitters can detect the NPW to identify the leak. According to the time difference between the NPW reaching the upstream and downstream sensors, the leak position can be determined. However, the NPW method may be influenced by

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background noise. In addition, the measured pressure signal is usually nonstationary and nonlinear with noise. The leak characteristics are easily lost if the noise reduction is poor, which will in turn affect the accuracy of leak detection and location [10]. At present, local mean decomposition (LMD), which is a new nonlinear and nonstationary signal processing method proposed by Smith [11], has been widely used for noise reduction in pipeline leak detection and location. The method can decompose the original signal into several physical PFs, which preserve more signal frequency and envelope information. However, LMD has some shortcomings in practical applications. For example, LMD calculates the local mean function and the envelope estimation function with low accuracy and boundary distortion, which make an influence on noise reduction of original signals. Deng and Zhao [12] proposed a spline-local mean decomposition (SLMD), which used cubic spline interpolation instead of the moving average to calculate the corresponding local mean function and envelope estimation function. The boundary distortion in calculating the upper and lower envelopes is overcome by using an adaptive waveform matching technique to appropriately extend the original signal. Although SLMD has higher accuracy and efficiency than LMD, it cannot reasonably select the PFs component containing target information [13]. Conventional LMD selects the PF based on frequency, but the frequency of the noise and leak signals in the pipeline are unknown. Furthermore, the frequency varies with operating conditions and environment. Lang *et al.* [14] proposed an improved LMD (ILMD) to select the PFs component. The method determines whether the PF is noise according to the cross-correlation between the PF and the reference signal, and the method then completes signal filtering. In our study, an improved spline-local mean decomposition (ISLMD) is proposed that combines the characteristics of SLMD and ILMD. The proposed method provides better accuracy than ILMD and is more reasonable in selecting PF than SLMD.

Leak detection usually extracts features from noise-reduced signals and performs machine learning on signal characteristics. For example, the pressure wave feature vector was extracted and used as the input of least squares support vector machine (LSSVM) to detect pipeline leaks [14]. In our experiments, we have found that the extracted feature vectors are very alike under different leak positions and different leak apertures. The similar characteristics will affect the accuracy of different leak aperture detection. Most existing research methods only discussed different leak apertures at one position and did not consider the randomness of the leak location. Conversely, under different leak positions with the same leak aperture, the leak pressure changes have a similar wave, which can be used to recognize different leak apertures. In this work, the convolutional neural network (CNN) that is an algorithm commonly used in pattern recognition will be considered to detect different aperture leaks. CNN not only has good generalization ability but also has good accuracy for multi-classification. Especially, CNN has obvious advantages in dealing with 2-dimensional image data [15], [16]. It should be emphasized that CNN takes images as input and not only avoids subjective and complex data feature extraction but also does not require excessive human participation in image feature extraction and learning [17].

In this paper, the pressure signals under different leak apertures and positions are collected and decomposed into a list of PFs by SLMD. By calculating the cross-correlation function between each PF and the reference signal, PFs containing leak information are selected using the proposed ISLMD method. Then, the selected PFs are reconstructed, and the noise is further filtered by wavelet analysis for the reconstructed signal. On this basis, the signals are converted into images as inputs of the AlexNet model for training. Thus, the model can be obtained with application to leak detection. Finally, the leak time delay is determined by the generalized cross-correlation coefficient of the upstream and downstream pressure signals whereby the leak location can be calculated.

II. METHODOLOGY

A. ISLMD METHOD

For nonlinear and nonstationary signals, the formulation of SLMD decomposition can be expressed by

$$x(t) = \sum_{i=1}^{k} \mathrm{PF}_i + r_k(t) \tag{1}$$

where k is the number of PF and $r_k(t)$ is the residue. By using the SLMD algorithm, the original signal can be decomposed into a series of PFs, each of which is the product of an envelope signal and a purely frequency modulated signal, where the former expresses the change in signal amplitude, and the latter represents signal frequency. In fact, PFs has been proven having more reasonable and meaningful explanations. Generally, noise is the high-frequency signal. The noise in $x(t)$ can be removed by carefully selecting PFs and $r_k(t)$ according to frequency. However, the noise frequency is unknown in the actual working conditions and will change with the working conditions and materials of the pipeline, which makes it difficult to reasonably select PFs. Therefore, this paper proposed an improved SLMD that selects the PFs by introducing a reference signal.

The upstream pressure signal $x_u(t)$ is considered as the major signal, and the downstream pressure signal $x_d(t)$ is considered as the reference signal, or vice versa. $x_u(t)$ and $x_d(t)$ can be expressed by Eq. (2).

$$\begin{cases} x_u(t) = \alpha\bar{x}(t-\tau_1) + n_1(t) \\ x_d(t) = \beta\bar{x}(t-\tau_2) + n_2(t) \end{cases} \tag{2}$$

where $\bar{x}(t)$ is the original leak signal, τ_1 and τ_2 are the time-delay, α and β are the attenuation factors of the leak original signal propagating along the pipeline, $n_1(t)$ and $n_2(t)$ are uncorrelated random noises. According to Eq. (1), the upstream measurement signal $x_u(t)$ is decomposed into PFs and $r_k(t)$ using SLMD, which will be used to make a correlation analysis with the reference signal $x_d(t)$. In the ideal condition, if the cross-correlation function $R_i = 0$, the PF_i component is noise. Otherwise, the PF_i component is leak signal. The correlation analysis can be expressed by Eq. (3).

$$\begin{cases} R_i(\tau) = \int_0^T PF_i^{noise} x_d(t+\tau) = 0 \\ R_j(\tau) = \int_0^T PF_i^{signal} x_d(t+\tau) \neq 0 \end{cases} \tag{3}$$

The reconstruction signals $\tilde{x}(t)$ by selecting PF_i^{signal} can be described as

$$\tilde{x}(t) = \sum PF_i^{signal}(t) \tag{4}$$

However, in actual working conditions, the cross-correlation function of two unrelated signals is impossible exactly equal to zero. If there is a significant peak in the correlation coefficient function between a certain PF_i and the reference signal, and most of the data is much smaller than the peak (maximum) in the cross-correlation function, then the PF_i contains leakage information. Inversely, When the cross-correlation function has no distinct peak, there is no significant difference between the maximum and minimum values (they are roughly equal), then the PF_i can be considered noise. According to this principle, we define a PF correlation factor to select PFs. This factor can be expressed by Eq. (5).

$$\delta = \sqrt{\frac{1}{T}\sum_{\tau=1}^{T}(|\max(R(\tau))| - |R(\tau)|)^2} \tag{5}$$

The appropriate threshold δ_0 should be selected for the PF correlation function. When $\delta \geq \delta_0$, the PF_i component is considered as the leak signal; and when $\delta < \delta_0$, the PF_i component is noise.

Nevertheless, the reconstructed pressure signal may still contain fine burrs after ISLMD noise reduction, which will affect the accuracy of image leak detection. Therefore, the reconstructed signal is further decomposed by wavelet transform to remove the wavelet coefficients corresponding to the noise. The proposed algorithm flowchart of noise reduction is shown in Fig. 1.

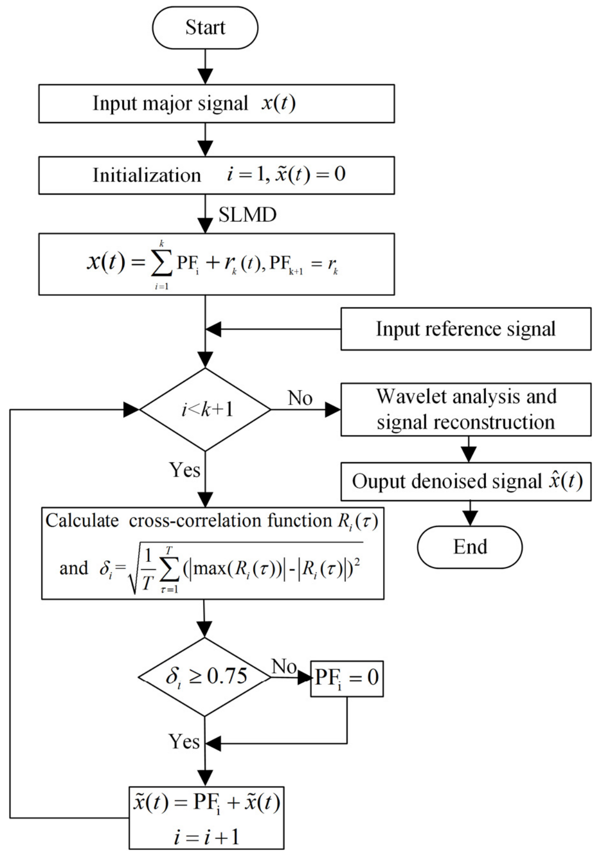

FIGURE 1. The flow chart of noise reduction.

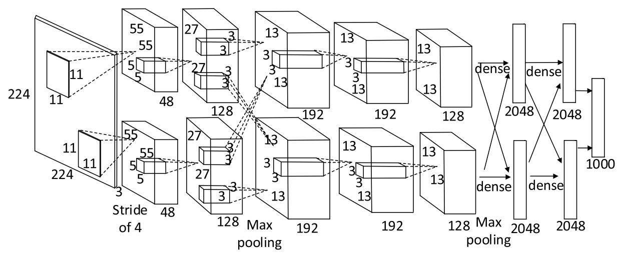

FIGURE 2. AlexNet structure diagram [18].

B. LEAK DETECTION BASED ON CNN

CNN has a good effect on visual recognition. From the 1980s to the 1990s, CNN was simply applied to handwritten digit recognition. Until 2012, Krizhevsky *et al.* [18] used the extended CNN to achieve the best classification effect in ISVRC (ImageNet Scale Visual Recognition Challenge). From then on, the CNN has received increasingly attention. The CNN generally includes convolutional layers, pooling layers (also referred to as sampling layers), fully connected layers, and an output layer [19].

The CNN model used in this paper is AlexNet [18], and its structure is shown in Fig. 2. The model has 5 convolutional layers, 3 fully connected layers, with the first, second and fifth convolutional layers having a pool pooling layer and the others without pooling layers.

AlexNet model uses the difference in leak pressure signal changes to detect different leak apertures. The different images of leak aperture are input into the CNN for training, and then the pipeline leak aperture recognition model is tested and established.

The proposed algorithm flowchart of leak detection and location is shown in Fig. 3.

III. SIMULATION STUDY

A. DATA GENERATION BY FLOWMASTER SOFTWARE

In our experiment, the pipeline leakage scenarios and pipeline model are established by the use of Flowmaster software [20]. As shown in Fig. 4, a length of 1510 m water pipeline

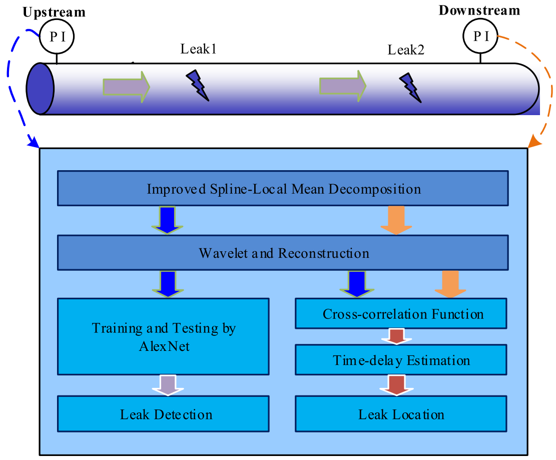

FIGURE 3. Flow chart of detection and location.

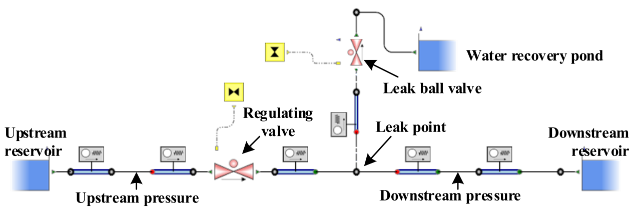

FIGURE 4. Pipeline simulation design.

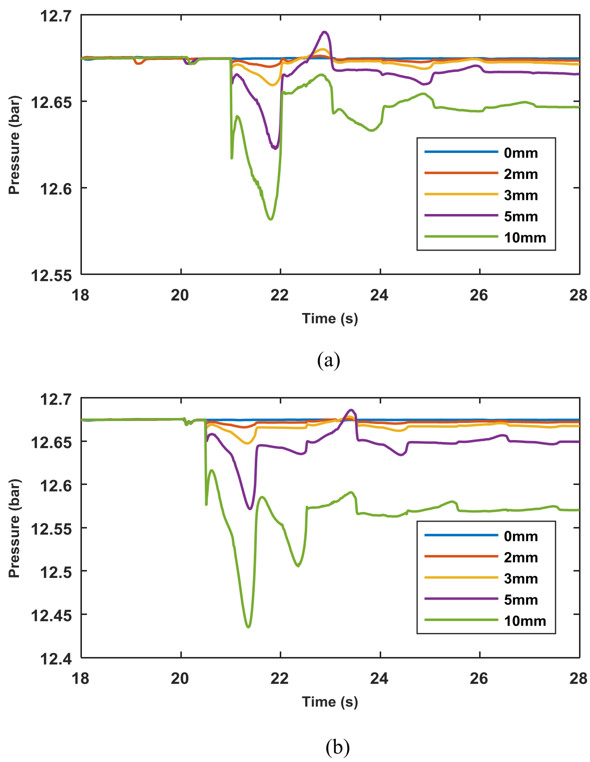

FIGURE 5. Experiment result. (a) Dynamic process of the upstream pressure from pipeline upstream reservoir 1000 m with different leakage apertures. (b) Dynamic process of the upstream pressure from pipeline upstream reservoir 500 m with different leakage apertures.

bounded by an upstream node and a downstream node is considered. The pipeline setting parameters are as follows: the inner diameter is 0.05 m; the relative wall roughness in

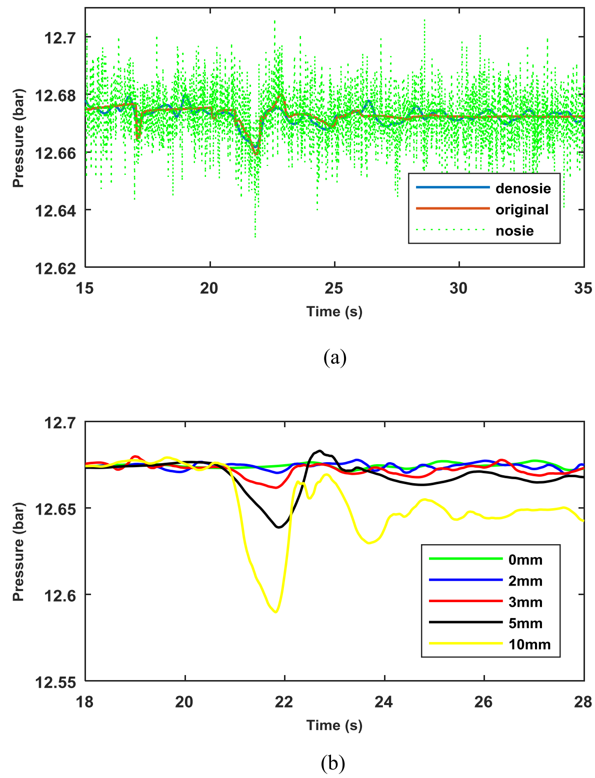

FIGURE 6. Upstream signal from pipeline upstream reservoir 1000 m noise reduction diagram. (a) Comparison of upstream pressure reconstructed signal of 3 mm leak aperture. (b) Comparison of upstream pressure reconstructed signal of different leak apertures.

the pipe is 0.025 mm, and the drops of upstream reservoir and downstream reservoir are 120 m; the negative pressure wave propagation speed is assumed as 1000 m/s, and the temperature is 20 degrees Celsius. To simulate the leak of different positions, the distance between the leak position and the upstream reservoir is set to 1000 m and 500 m, respectively. To simulate the different leak apertures, a flow ball valves is installed on the pipeline between the upstream reservoir and downstream reservoir. And the leak aperture is set to 0 mm, 2 mm, 3 mm, 5mm and 10 mm, respectively. There are two pressure sensors installed for the measurements of the upstream and downstream pressures, and the sampling frequency is 100 Hz. The simulation time is 40 s, the regulating valve is opened in 2 s, and the leak ball valve is opened in 20 s. the experiment results are shown in Fig. 5.

B. SIGNAL PROCESSING AND IMAGE GENERATION

To simulate the actual working condition of the pipeline, Gaussian noise (average of 0 and variance of 0.01) is added to the upstream and downstream pressures. Decomposing the upstream pressure signal by SLMD, the PF component containing the leak signal are selected and reconstructed by setting the PF correlation factor threshold $\delta_0 = 0.75$. The reconstructed signal uses wavelet analysis (db4 wavelet, 7 layers), and the threshold of the 6th and 7th layers is 0. The denoising result of the pressure signal of 1000 m from the upstream reservoir is shown in Fig. 6. 2000 sets of data are

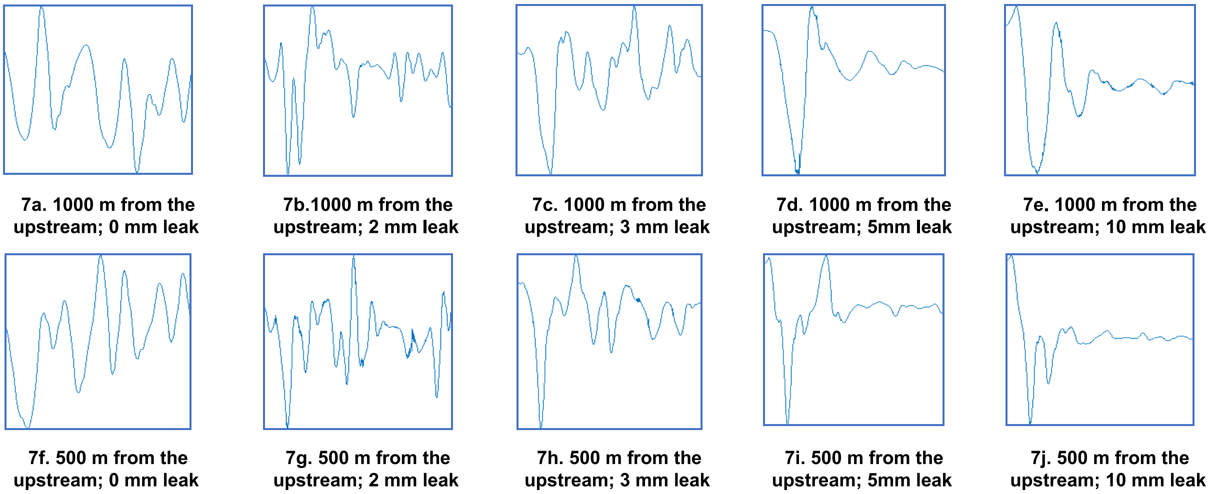

FIGURE 7. Images for AlexNet training and test. (a) 1000 m from the upstream; 0 mm leak. (b) 1000 m from the upstream; 2 mm leak. (c) 1000 m from the upstream; 3 mm leak. (d) 1000 m from the upstream; 5mm leak. (e) 1000 m from the upstream; 10 mm leak. (f) 500 m from the upstream; 0 mm leak. (g) 500 m from the upstream; 2 mm leak. (h) 500 m from the upstream; 3 mm leak. (i) 500 m from the upstream; 5mm leak. (j) 500 m from the upstream; 10 mm leak.

generated with each leak aperture by simulating 200 times from the upstream 1000 m and 500 m, respectively. Without loss of generality, all curves have been set to the same color and size during the image generation, and any marks are erased that are not related to pressure wave. The pixel setting is 227*227. In our study, only the color of blue is used (i.e., the values of red and green are set to zeros), which makes the operation simpler and has more efficient calculation speed. Fig. 7 gives a serial of generated pictures of different leak apertures with distances of 1000 m and 500 m from the upstream, respectively.

It can be seen in Fig. 7 that the pressure variations of different leak apertures are different at the same distance. In the cases of no leak, the waveform shows a zigzag shape and the pressure oscillates back and forth. For the occurrence of leak, there is a distinct peak and valley. Moreover, the dynamic processes after the peaks and valleys are different. Compared to the small leak, the processes are more stable after the peaks and valleys. The reason for this phenomenon is that the larger negative pressure wave is generated as a result of the larger leak.

IV. DETECTION AND LOCATION

A. LEAK RECOGNITION BASED ON AlexNet

The AlexNet model is trained by using a momentum-based stochastic gradient descent method, and the classical stochastic gradient descent method based on reversed propagation algorithm is used to adjust model parameters. The initial learning rate is set to 0.001, and MaxEpochs is set to 20. MiniBatchSize is set to 64. The ratio of training data and test data is 8:2. Fig. 8 shows a test sample with a leak-free pressure map at a distance of 1000 m from the pipeline upstream reservoir and each convolution layer output feature extraction map.

In the study, the least squares support vector machine (LSSVM) is selected in order to compare with the

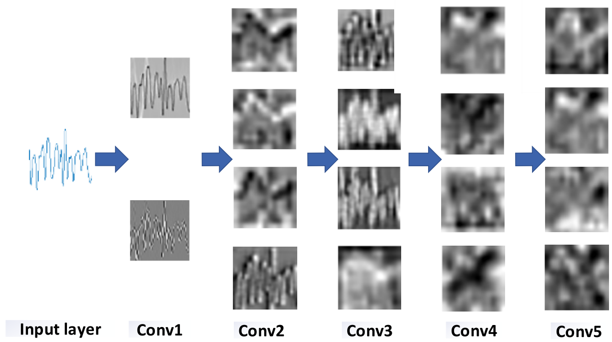

FIGURE 8. Output feature maps of a particular test sample.

performance of the proposed method for leak detection. The above pressure signals are first extracted and then input into the LSSVM. The extracted features of LSSVM include: RMS X_{am}, variance X_s, energy E, kurtosis X_k, turbulence factor X_l and pulse factor X_{imf}, and the calculation formulas of these features can be found in the literatures [5], [21].

$$X_{\mathrm{am}} = \frac{1}{n}\sum_{i=1}^{n}|x_i| \tag{6}$$

$$X_{\mathrm{s}} = \frac{1}{n}\sum_{i=1}^{n}(x_i - x_{am})^2 \tag{7}$$

$$E = \sqrt{\frac{1}{n}\sum_{i=1}^{n}x_i^2} \tag{8}$$

$$X_k = \left(\frac{1}{n}\sum_{i=1}^{n}x_i^4\right)^{1/4} \tag{9}$$

$$X_l = \min(|x_i|)/\left(\frac{1}{n}\sum_{i=1}^{n}|x_i|^{0.5}\right)^2 \tag{10}$$

$$X_{imf} = \max(x_i)/X_{am} \tag{11}$$

TABLE 1. Feature extraction with different leak apertures for LSSVM.

	Operation condition	X_{am}	X_s	E	X_k	X_l	X_{imf}
1000 m	normal	37.4430	0.0314	37.4434	37.4442	0.9885	1.0076
		37.4737	0.0060	37.4737	37.4739	0.9965	1.0036
	2 mm Leak aperture	37.3654	0.0512	37.3661	37.3675	0.9893	1.0163
		37.3839	0.0466	37.3846	37.3858	0.9904	1.0153
	3 mm Leak aperture	37.1379	0.2625	37.1415	37.1484	0.9661	1.0184
		37.1742	0.1956	37.1768	37.1820	0.9664	1.0158
	5mm Leak aperture	36.5978	1.3235	36.6158	36.6509	0.9247	1.0468
		36.5726	1.2114	36.5892	36.6215	0.9279	1.0579
	10 mm Leak aperture	34.7193	4.7759	34.7879	34.9222	0.8853	1.1015
		34.6393	4.4872	34.7039	34.8308	0.8883	1.1045
500 m	normal	37.4699	0.0147	37.4701	37.4705	0.9920	1.0090
		37.4389	0.0319	37.4393	37.4401	0.9895	1.0106
	2 mm Leak aperture	37.1911	0.0668	37.1920	37.1938	0.9887	1.0094
		37.1300	0.0372	37.1305	37.1315	0.9890	1.0114
	3 mm Leak aperture	36.6984	0.3878	36.7037	36.7141	0.9589	1.0284
		36.6365	0.4216	36.6422	36.6535	0.9545	1.0320
	5mm Leak aperture	34.8197	3.1085	34.8642	34.9498	0.8543	1.0809
		34.6394	3.5312	34.6902	34.7852	0.8270	1.0791
	10 mm Leak aperture	27.0254	19.4615	27.3824	28.1073	0.0071	0.6109
		27.0191	20.1501	27.3887	28.1265	0.0071	0.5900

TABLE 2. Comparison result of leak detection.

Method	Accuracy	
	1000 m	500 m
AlexNet	92.5%	85.6%
LSSVM	91.5%	79.15%

For the sake of simplicity, only two sets of extracted features are selected stochastically for each operation condition. For better feature extraction, the denoised pressure signals are subtracted by 12.3 bar and magnified 100 times. The feature extraction from the upstream 1000 m and 500 m leaks is shown in Table 1.

As shown in Table 1, some feature vectors are very close to each other under different positions or different apertures. These close eigenvectors could reduce the performance of LSSVM to recognize different leak categories.

The ratio of the training set and the test set for LSSVM is the same as the AlexNet. When the leak position occurs at 1,000 m from the upstream of pipeline, the comparison of leak detection result with the AlexNet and LSSVM methods is shown in column 2 of Table 2. At the same time, in order to compare the model generalization ability, the models obtained from upstream 1000 m are used to detect the leak from upstream 500 m. The specific results are shown in column 3 of Table 2, where AlexNet demonstrates higher accuracy than LSSVM at 1000 m, and the model has good generalization ability at 500 m.

B. LEAK LOCATION

The downstream pressure signal with different apertures from the pipeline upstream reservoir 1000 m is processed in the same manner as the upstream signal, and the result of denoising is shown in Figs. 9a-9d.

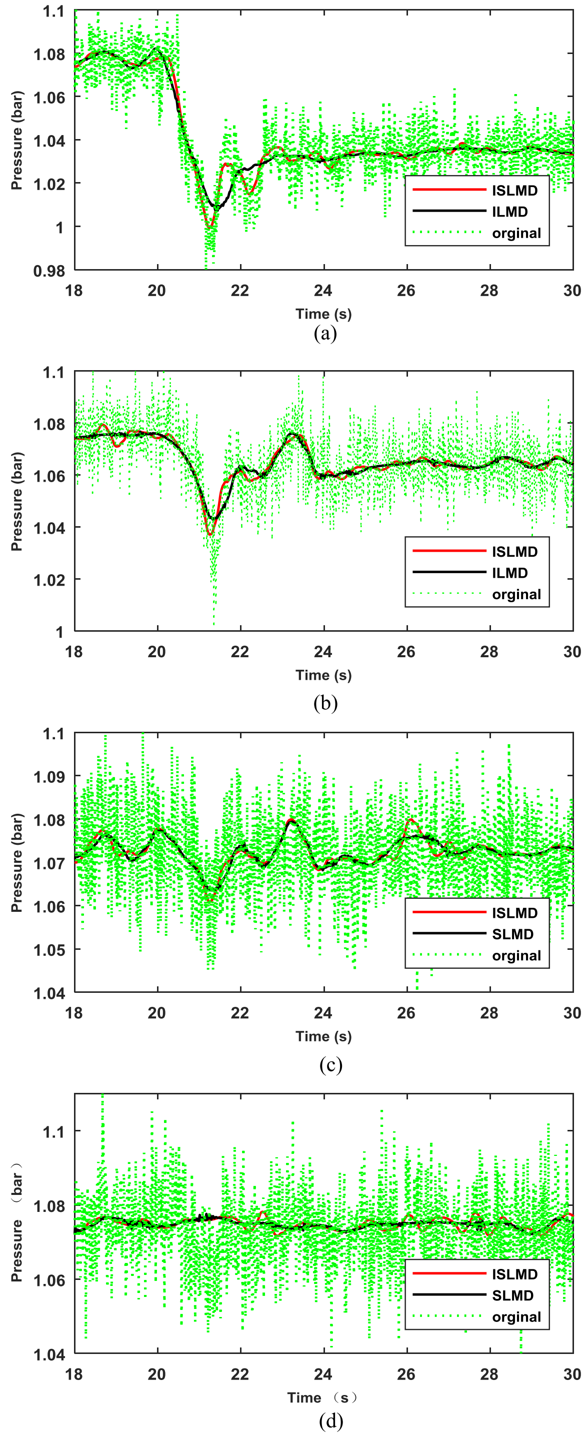

FIGURE 9. Processing results of downstream pressure signals. (a) 10mm leak aperture. (b) 5mm leak aperture. (c) 3 mm leak aperture. (d) 2 mm leak aperture.

To find out the leak location, the pressure signal time delay between the upstream and downstream pressure sensors resulted from the pipeline leak and propagation of negative pressure wave should be obtained. The generalized correlation analysis method is adopted to calculate the time delay.

TABLE 3. Leakage localization results with different approaches.

Method	Leak aperture	Predicted location	Absolute error
ISLMD	2 mm	1114.7 m	114.7 m
	3 mm	1070.6 m	70.6 m
	5mm	1050.1 m	50.1 m
	10 mm	1038.5m	38.5m
ILMD	2 mm	1138.0m	138 m
	3 mm	1090.2 m	90.2 m
	5mm	1070.0m	70.0m
	10 mm	1050.3 m	50.3 m

In a similar manner to PFs' selection, when there is a significant peak in the generalized cross-correlation function of the upstream and downstream pressure signals, the time delay can be obtained by calculation. And thus, the leak position is calculated according to Eq. (12).

$$L_x = (L + v \times \Delta t)/2 \tag{12}$$

The leak point L_x is from the upstream reservoir, and L is the length of the pipe. v is the propagation speed of negative pressure wave, and Δt is the time difference. The comparison results with ILMD are shown in Table 3, where the predicted location is the mean of the 20 groups selected randomly. The results show that ISLMD has higher accuracy and smaller absolute error than ILMD.

V. DISCUSSION AND CONCLUSIONS

Pipeline leak pressure is a nonstationary, nonlinear signal. The proposed ISLMD method can effectively deal with signal denoising, and then the different leak apertures can be achieved by AlexNet. Moreover, the experimental results showed that AlexNet can distinguish different leak apertures in different leak point and has higher accuracy and better generalization ability than LSSVM. For the location of a pipeline leak, the time-delay can also be effectively estimated by a generalized cross-correlation function based on the reconstruction signal that used the proposed ISLMD. The experimental results showed that ISLMD has higher location accuracy than ILMD. However, the ISLMD and ILMD should be needed to further improve for small leaks (e.g., 2 mm leak aperture). Conversely, although AlexNet can adaptively extract image feature extraction and has higher accuracy compared with LSSVM, the AlexNet model requires a large amount of training data and high performance on computer hardware. These issues will be further studied in future research.

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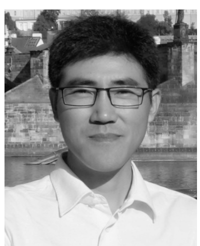

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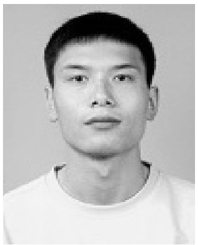

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