

A Novel Leak Localization Method for Water Pipeline Systems Based on Acoustic Emission Monitoring and Event Correlation

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Abstract. This paper proposes a novel method for leak localization in water pipeline systems through the monitoring of acoustic emissions and cross-correlation of acoustic emission events. The method is designed to overcome limitations in the calculation of the time difference of arrival by traditional methods such as time-of-arrival detection and cross-correlation. The proposed method combines these two conventional techniques, specifically by examining cross-correlation at positions associated with arrived acoustic emission events. The positions of acoustic emission events are initially identified using the constant false alarm rate signal detection algorithm. Subsequently, the minimum entropy deconvolution is applied at these positions to eliminate noise and reveal signal information. Finally, cross-correlation at the identified positions is computed to determine the time difference of arrival and localize the leak position. Experimental validations on a real-world testbed demonstrate the effectiveness of the proposed method with a high level of accuracy. The proposed method exhibits superior accuracy in comparison to other methods.

Keywords: Leak Localization · Pipeline Systems · Acoustic Emission · Constant False Alarm Rate · Minimum Entropy Deconvolution

1 Introduction

Water pipelines play a vital role in both industrial activities and daily life [1]. Monitoring the condition, detecting, and precisely locating leaks in water pipelines are crucial for minimizing resource losses and ensuring community safety [1, 2]. Current methods for pipeline monitoring include pressure and flow monitoring, acoustic emission monitoring, and image inspection [3]. While pressure and flow monitoring can detect significant leaks, they are less effective for small leaks and challenged in accurately pinpointing the leak location [4, 5]. Image inspection becomes even more challenged when dealing with buried pipes or limited access spaces [6, 7]. Acoustic emission (AE) monitoring is considered suitable for effectively detecting and precisely locating leaks in pipelines due to its high sensitivity and quick response [8]. Recent studies in AE monitoring have

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demonstrated its efficiency [9–12], leading to the focus of this research on deploying AE monitoring for leak localization in water pipelines.

The general principle for leak localization involves using two AE sensors placed at the ends of the pipeline to record AE events caused by leaks [12]. The leak position is then determined either based on amplitude differences or the time difference of arrival (TDOA) of the AE events [12, 13]. The first approach requires knowledge of signal attenuation characteristics and consideration of environmental noise effects, presenting challenges due to their inherent instability [14]. Current research often emphasizes the second approach, which involves determining the TDOA [12, 15–17]. Once TDOA is calculated, the difference in distance of the wave travelled can be easily determined based on the wave propagation velocity. It leads to the identification of the source of the AE event i.e., leak location. This approach is simple, highly effective, and easily applicable in practical scenarios, making it a focal point in this study.

In general, there are two main methods for determining TDOA: time of arrival detection and cross-correlation [12]. For the first method, the crucial aspect is accurately determining the arrival time of each acoustic emission event and calculating the time difference between two sensors [18]. This task appears complex and demands precision, as even a slight deviation in arrival time can result in significant errors in predicting the leak location. Moreover, if consecutive AE events occur with overlapping, determining the time of arrival becomes impractical [19]. The second method calculates the cross-correlation of signals between two sensors to find TDOA, identifying the shift time where the correlation is the highest [17, 20]. While this method is simple and highly accurate, it cannot confirm whether there are AE events in the signal or not. Considering the limitations of these two methods, this study aims to propose a hybrid method that leverages the advantages and mitigates the drawbacks of both methods.

The proposed approach involves first detecting AE events in the signal and then using cross-correlation at the positions of the detected events. It eliminates the need for detailed time-of-arrival calculations, taking advantage of the simplicity and effectiveness of cross-correlation. This constitutes the main idea of this research. Specifically, a constant false alarm rate (CFAR) signal detector [21] is initially employed to identify positions with AE events, referred to as AE-active positions. Subsequently, to eliminate noise and reveal signal information, finite impulse response (FIR) filters based on minimum entropy deconvolution (MED) [22] are applied at AE-active positions. The MED is performed after CFAR detection as it is effective only for single AE events identified by CFAR. Finally, cross-correlation is computed at the AE-active positions of two sensors to determine TDOA. Based on the calculated TDOA and known wave propagation velocity, the leak position is determined.

The contributions of this article can be summarized as follows:

- Introducing a novel hybrid method combining time-of-arrival and cross-correlation for leak localization in water pipelines. The proposed method leverages the advantages and addresses the limitations of traditional methods.
- Experimental validations conducted on a real-world testbed to confirm the effectiveness of the proposed method and its superiority over other methods.

2 Background Concepts

2.1 Constant False Alarm Rate Detection

Constant false alarm rate (CFAR) detection is applied in this article to detect AE events caused by leaks. The CFAR detection is a critical aspect of radar signal processing designed to dynamically adjust target detection thresholds in response to varying environmental conditions [23]. In CFAR, cells, or resolution cells, are defined, with a specific cell under test (CUT) selected for target determination. CFAR algorithms calculate the statistical properties of the local environment surrounding the CUT, considering neighboring cells in both range and azimuth. It includes constant false alarm rate-constrained estimation of background noise from the surrounding cells of the CUT, called training cells, but excluding the adjacent cells to the CUT, referred to as guard cells. This comprehensive estimation of background noise allows for the adaptive setting of a detection threshold that maintains a constant probability of false alarms.

Specifically, a configured sliding window includes CUT, guard cells, and training cells as depicted in Fig. 1. The sliding window scans the entire signal with a step equal to the length of CUT for threshold computation detection for each CUT. A CUT is considered to contain a signal if its amplitude exceeds the estimated threshold. The detection threshold for each CUT is determined as follows [23]:

$$T = P_n\left(P_{fa}^{-1/N} - 1\right) \tag{1}$$

where P_n is the sum of samples of training cells, P_{fa} is the constant false alarm rate, and N is the number of training cells. This formula is called cell averaging CFAR (CA-CFAR).

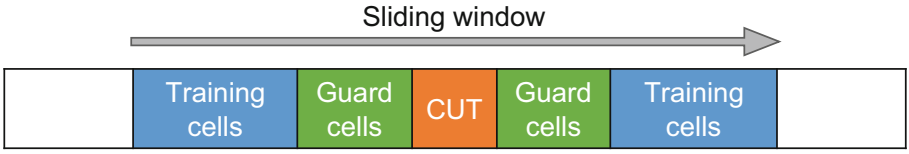

Fig. 1. Components of sliding window in CFAR detection.

2.2 Minimum Entropy Deconvolution

Minimum entropy deconvolution (MED) [22] stands out as a potent signal processing technique meticulously crafted to augment the resolution of signals intricately interwoven with convolutional noise. The core of MED revolves around the design of a finite impulse response (FIR) filter to extract the distinctive features of signals in the form of an impulse. The MED accomplishes this by iteratively fine-tuning the deconvolution process, aiming to maximize the kurtosis of the output signal and, consequently, optimizing its information content.

This concept aligns seamlessly with signals such as the vibrations of rotating machinery or acoustic emissions. However, its true efficacy shines when applied to signals

containing only a single impulse, thereby limiting its applicability. To address this limitation, in this research, MED is employed to filter individual AE events detected by CFAR, rather than processing the entire raw signal.

The methodology for implementing the MED-based filter in this context unfolds as follows. We denote $\vec{x} = \begin{bmatrix} x_1 \; x_2 \; \dots \; x_N \end{bmatrix}^T$ as the input signal (detected AE event), $\vec{y} = \begin{bmatrix} y_1 \; y_2 \; \dots \; y_N \end{bmatrix}^T$ as the output filtered signal, and $\vec{f} = \begin{bmatrix} f_1 \; f_2 \; \dots \; f_K \end{bmatrix}^T$ as the impulse response FIR filter. For a causal discrete-time FIR filter, the signal model is represented as in (2), (3):

$$\vec{y} = \vec{f} * \vec{x} = X^T \vec{f} \tag{2}$$

$$X = \begin{bmatrix} x_1 & x_2 & x_3 & \dots & x_N \\ 0 & x_1 & x_2 & \dots & x_{N-1} \\ 0 & 0 & x_1 & \dots & x_{N-2} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \dots & x_{N-K+1} \end{bmatrix}_{K \times N} \tag{3}$$

The objective of MED is to search for the filter $\vec{f}$ that maximizes the kurtosis of the output signal. This process is formalized in Eq. (4), assuming a zero-mean output $\vec{y}$ [22]:

$$\max_{\vec{f}} \frac{\sum_{n=1}^{N} y_n^4}{\left(\sum_{n=1}^{N} y_n^2\right)^2} \tag{4}$$

The search process is carried out to find a favorable solution using the Wiggins algorithm [22]. It involves computing the derivative of the kurtosis objective function and then solving the derivative equation with respect to the filter vector $\vec{f}$ iteratively through numerical methods. The iterative selection of $\vec{f}$ derived by Wiggins is outlined in Eq. (5) [22]:

$$\vec{f} = \frac{\sum_{n=1}^{N} y_n^2}{\sum_{n=1}^{N} y_n^4} \left(XX^T\right)^{-1} X \begin{bmatrix} y_1^3 \; y_2^3 \; \dots \; y_N^3 \end{bmatrix}^T \tag{5}$$

Accordingly, the initial value of $\vec{f}$ is selected as the centered initial difference filter to compute the initial output $\vec{y}$. Using Eq. (5), the initial $\vec{y}$ is then employed to calculate the updated filter $\vec{f}$, which, in turn, is used to compute a new $\vec{y}$. The termination criteria for this iterative process are commonly defined as a minimum change in filter coefficients between successive iterations [24].

3 Methodology

This section presents the proposed method for addressing the water pipeline leak localization problem. The condition monitoring model utilizes two AE sensors installed at the ends of the pipeline to locate leaks between the two sensors. Figure 2 illustrates the detailed workflow of the implementation steps, which are elaborated as follows:

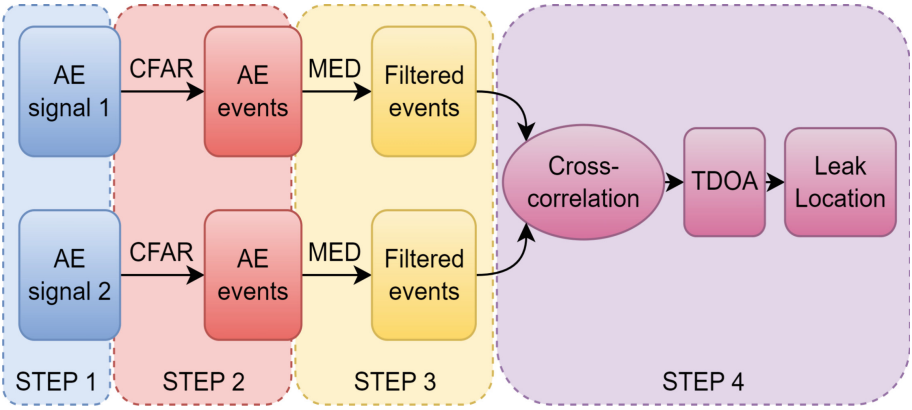

Fig. 2. The workflow of the proposed method.

- Step 1: AE signals are collected from the two AE sensors placed at the ends of the pipeline. It is assumed that the received signals represent the signal at the time the leak occurred.
- Step 2: The CA-CFAR detection algorithm is applied to both received signals to determine the positions of AE events. Specifically, a sliding window is chosen with a CUT size of 1 ms, 4 guard cells (4 ms), and 10 training cells (10 ms). The desired false alarm rate is set to 10^{-6} to ensure the reliability of the detection results. Figure 3 illustrates the use of CA-CFAR for AE event detection, showing an adaptive detection threshold (red line) that accurately identifies AE events, as observed in the grey boxes.
- Step 3: FIR filters based on MED are employed to clean the detected AE events. This is done to reveal the information of the AE signals for accurate cross-correlation calculation. Specifically, filters of length 50 are used for each AE event to find the most suitable filters. Figure 4(a) illustrates the result of using the FIR filter based on MED to clean an AE event, with the optimal filter found in Fig. 4(b). It can be observed that the filtered signal significantly reduces background noise, aiding in minimizing the impact of noise on AE signals and enhancing accuracy for subsequent cross-correlation calculations.
- Step 4: The filtered AE events are input into cross-correlation calculations to determine the TDOA. Specifically, AE events at sensor 1 are cross correlated with neighboring AE events at sensor 2. Neighboring events are defined as those occurring within a time interval not exceeding D/v seconds, where D is the distance between two sensors, and v is the wave propagation velocity ($v = 2600$ m/s in this work). This ensures that the predictions of leak location are positioned between the two sensors. Afterwards, TDOA is determined by the lag time (Δt) where the correlation value is maximum. Finally, the leak location is calculated using the following formula:

$$x = \frac{D - v\Delta t}{2} \tag{6}$$

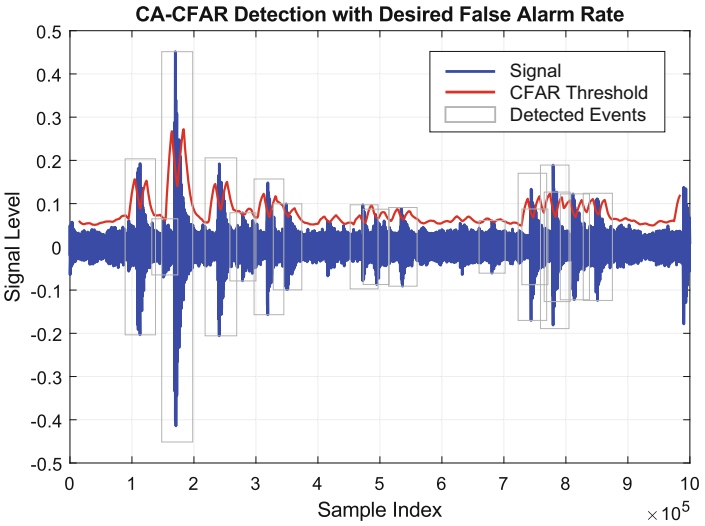

Fig. 3. Illustration of the use of CA-CFAR for AE events detection. (Color figure online)

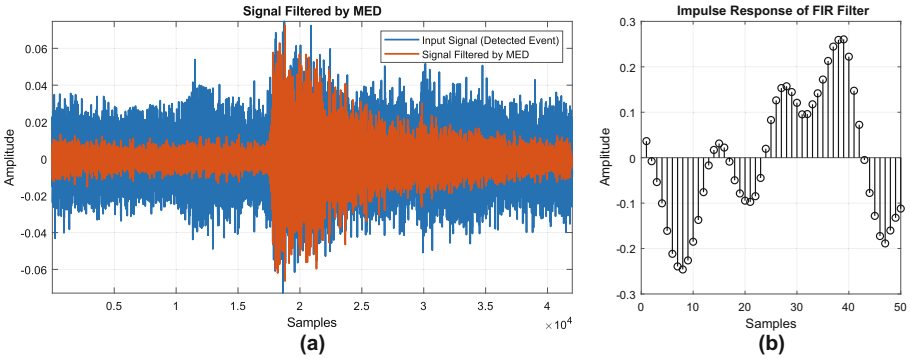

Fig. 4. Illustration of the use of MED for a detected AE event filter: (a) filtered signal, and (b) impulse response of the filter.

4 Experimental Setup

This section details the experimental scenarios conducted to validate the efficacy of the proposed method. Initially, a laboratory-based testbed simulating a water pipeline system was set up, as illustrated in Fig. 5 and Fig. 6. The testbed comprised a pump system and a steel water pipeline. Two R15I-AST AE sensors were strategically placed at the ends of the pipeline, separated by 2.5 m, with specification listed in Table 1. Leakage was simulated by welding perforated screws into the pipeline at a position 1.7 m from sensor 1. A data acquisition (DAQ) module (NI-9223) and a computer were deployed on-site to collect AE signals from the sensors. This experimental setup allows for validation of the proposed leak localization method under realistic conditions. The configuration

replicates a simplified yet representative scenario of a water pipeline system, facilitating the performance evaluation of the proposed method.

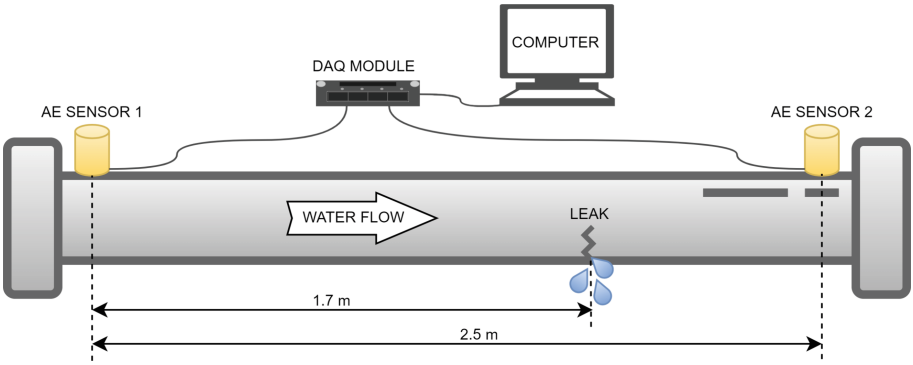

Fig. 5. Experimental testbed for leak simulation in a water pipe.

Table 1. Specification of AE sensors in the testbed.

Parameter	Value	Unit
Peak sensitivity	109	dB
Operating frequency	50 to 400	kHz
Resonant frequency	75	kHz
Directionality	±1.5	dB
Operating temperature	–35 to 75	°C

The data collection scenario unfolded as follows: initially, the pipeline was filled with water to achieve the desired pressure. Subsequently, leaks were activated, and data acquisition commenced for 100 s at a sampling rate of 1 million samples per second (1 MHz). Two leak sizes of 0.3 mm and 0.5 mm, along with two preset pressures of 13 and 18 bar, were considered. Therefore, four datasets were obtained, denoted as follows: 0.3 mm at 13 bar (313), 0.3 mm at 18 bar (318), 0.5 mm at 13 bar (513), and 0.5 mm at 18 bar (518).

Validation experiments were performed on the collected datasets, and evaluation criteria included the estimation of probability density and relative error. To estimate the probability density of predicted leak locations, a kernel smoothing function was employed based on kernel density estimation (KDE) methods [25]. The kernel density estimator can be defined as follows [25]:

$$f(x) = \frac{1}{Nh} \sum_{k=1}^{N} G\left(\frac{x - x_k}{h}\right) \tag{7}$$

where x is the leak location variable, N is the number of observed (predicted) leak locations x_k, G is the Gaussian kernel smoothing function [26], and h is the bandwidth

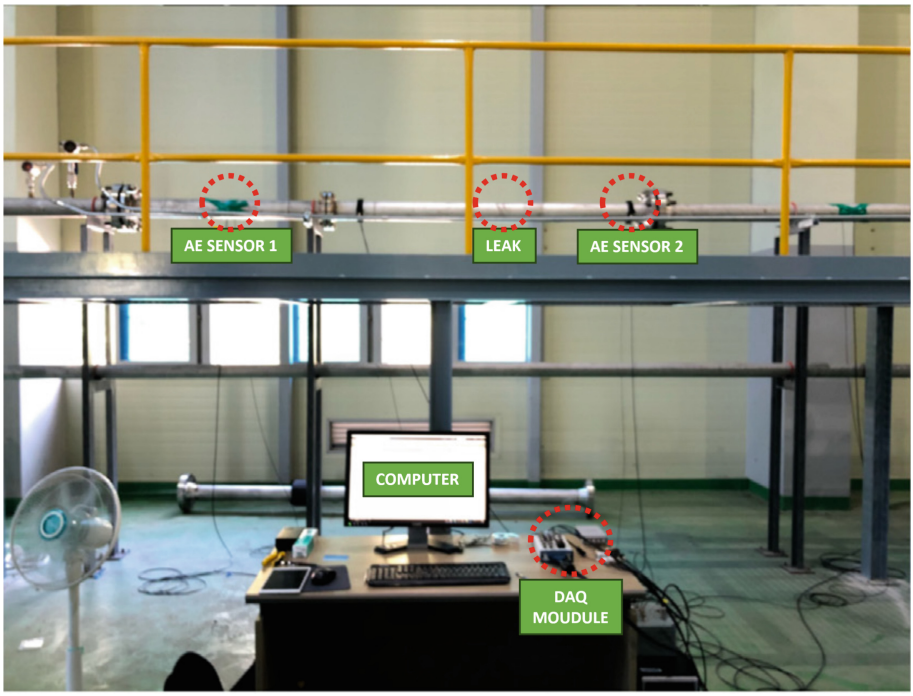

Fig. 6. Actual testbed system in laboratory.

determined based on the Silverman rule of thumb [27]. Subsequently, the final leak location was determined at the point with the highest density from the estimated probability density. This value was then used to compute the relative error according to the following formula:

$$\delta\% = \frac{|x_{leak} - \hat{x}|}{D} \times 100\% \tag{8}$$

where x_{leak} is the true leak location, $\hat{x}$ is the predicted leak location, and D is the distance between two sensors.

5 Results and Discussion

This section presents the results of experimental verification of the effectiveness of the proposed method, including predictive outcomes and comparisons with other popular methods. Figure 7 illustrates the predicted leak locations through a histogram of leak location predictions across four datasets. In each case, the estimated probability density is depicted to identify the concentration of predictions. Accordingly, the proposed method suggests leak positions extremely close to the actual leaks, with the highest density consistently above 1, near the position of 1.7 m. This observation demonstrates the efficacy of our method in accurately pinpointing leak locations. This achievement is

attributed to our approach fully leveraging the strengths of traditional methods. Additionally, all predictions fall within the range of 0 to 2.5 m, as the cross-correlation is constrained to select event pairs within proximity.

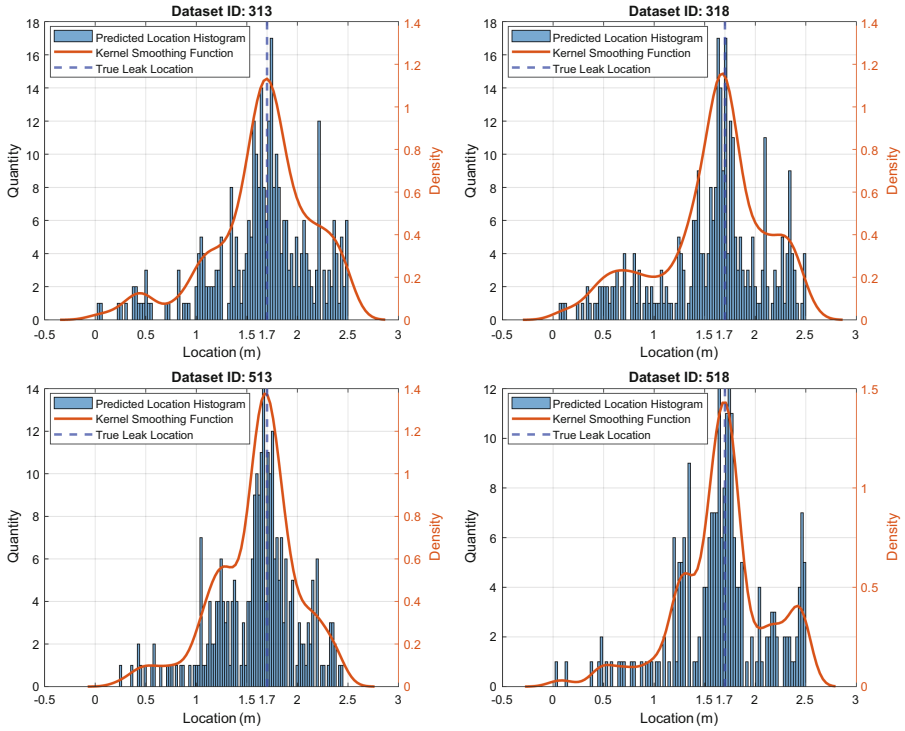

Fig. 7. Histogram and estimated probability density of leak location predictions.

To reinforce the effectiveness of the proposed method, comparative experiments were conducted. The examined methods include: (i) traditional cross-correlation (traditional CC) by calculating cross-correlation on every 10 ms of signal to determine TDOA, and (ii) the proposed method without MED filter named CFAR-CC method. Comparing these methods affirms the superiority of the proposed approach across different aspects.

Table 2 presents a comparative analysis of three leak localization methodologies across four datasets. The traditional CC method displays varying leak position errors ranging from 2.4% to 18.4%, with the highest error occurring in dataset 313. CFAR-CC demonstrates enhanced accuracy, with errors ranging from 1.6% to 5.6%, underscoring the significant improvement resulting from the combination of CFAR and CC due to selective filtering during cross-correlation computation. Notably, the proposed method consistently surpasses the others by providing precise leak positions (1.68 m to 1.70 m) with minimal errors (0.0% to 0.8%). This achievement is attributed to the proposed approach, which integrates both CFAR and CC while leveraging a MED filter to enhance the

Table 2. Comparison between methods for leak localization on pipeline.

Method	Prediction Results	Dataset ID: 313	Dataset ID: 318	Dataset ID: 513	Dataset ID: 518
Traditional CC method	Location (m)	2.16	1.96	1.64	2.08
	Error (%)	18.4%	10.4%	2.4%	15.2%
CFAR-CC method	Location (m)	1.84	1.76	1.66	1.82
	Error (%)	5.6%	2.4%	1.6%	4.8%
Proposed method	Location (m)	1.70	1.68	1.68	1.69
	Error (%)	0.0%	0.8%	0.8%	0.4%

efficiency of cross-correlation calculations. These findings underscore the superior accuracy of the proposed method, highlighting its potential for advancing leak localization precision on water pipelines in comparison to alternative methodologies.

6 Conclusion

This paper introduced a novel and effective method for leak localization in water pipelines using acoustic emissions monitoring and cross-correlation of acoustic events. The proposed method addressed limitations inherent in traditional approaches by integrating and leveraging their respective advantages. Inheriting the merits of both CFAR and CC methods, the suggested approach demonstrated enhanced leak localization. Additionally, FIR filters based on MED were adeptly employed to appropriately enhance the accuracy of computational efficiency. Experimental validations were conducted on a laboratory testbed, and the results substantiated the effectiveness and precision of the proposed method in predicting leak locations. When compared to traditional CC and CFAR-CC, our method exhibited superior accuracy. This positions our proposed method as a promising approach for potential application in the industry.

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