

Article

Study on a High-Pressure Pipeline Micro-Leakage Detection Method Based on Background-Oriented Schlieren Measurement and Feature Matching

Hao Chen ^{1,2}, Rifeng Jin ³, Jiarui Zhang ¹ , Yuqing Peng ¹, Wen Bao ^{1,*} and Jian Wang ^{2,*}¹ School of Energy Science and Engineering, Harbin Institute of Technology, Harbin 150001, China; 18811397288@139.com (H.C.)² Beijing Gaojing Thermal Power Branch, Datang International Power Generation Co., Ltd., Beijing 100041, China³ China Datang Corporation Ltd., Beijing 100033, China

* Correspondence: baowen@hit.edu.cn (W.B.); cdtgjrd0008@126.com (J.W.)

Abstract

Online detection of micro-leakage in complex high-pressure gas pipeline networks is difficult to achieve using conventional methods. A high-pressure pipeline micro-leakage detection method based on background-oriented schlieren measurement and feature matching was proposed in this study to address this issue. Through the BOS measurement, the density distribution of the leakage fields was reconstructed through cross-correlation calculation and Poisson equation solving, which was further compared with numerical simulation results under specific operating conditions. The morphological characteristics of the jet field at different leakage pressures were revealed by comparing the density fields from different experimental conditions. Subsequently, the displacement field data were compressed into one-dimensional feature representations for structure-oriented matching of leakage-field characteristics, with temporal smoothing and a dual-threshold hysteresis strategy incorporated to improve matching robustness. The results show that the error in the peak density remains below 10%, which indicates good consistency between the background-oriented schlieren measurements and the numerical simulations. Meanwhile, the one-dimensional feature curve accelerates computation while retaining the dominant characteristics of the leakage field. The proposed framework achieves an area under the ROC curve of 0.992 and an average precision of 0.998. At the selected threshold of 0.650, the overall evaluation metric reaches 0.972, reflecting a favorable balance between sensitivity and reliability. Furthermore, the temporal stabilization strategy improves alarm continuity and suppresses chattering during detection.

Keywords: high-pressure pipeline; micro-leakage detection; background-oriented schlieren (BOS); feature matching; false alarm control



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1. Introduction

As a key infrastructure in energy systems and major industrial devices, large-scale special electrical equipment is an important carrier for realizing power production, conversion, transmission and distribution, and occupies a core position in national energy security and stable operation of industrial systems [1]. During the operation of large-scale special electrical equipment, the transportation and storage of various high-risk working media—such as hydrogen, ammonia, flammable oil, and high-temperature, high-pressure

steam—are involved [2]. These media are delivered through complex pipe networks and high-pressure storage tanks. Numerous components along the transmission path are subjected to long-term exposure to high temperatures, high pressures, corrosive environments, and mechanical vibrations, which inevitably pose risks of medium leakage due to sealing failure, weld cracking, or valve aging [3]. Once a leakage occurs, it can not only cause chemical pollution but, in severe cases, also trigger combustion or explosion accidents, endangering the safety of personnel on site and causing irreversible equipment damage [4].

In hydrogen and ammonia storage stations and critical oil and gas pipelines of power plants, leakage detection mainly relies on manual inspection and sensor deployment. Manual inspection cannot promptly locate and control the leakage source upon occurrence [5]. Meanwhile, sensor-based methods using parameters such as pressure, flow rate, and gas concentration can achieve local quantitative monitoring but face difficulties in complex facilities or large-scale pipeline networks due to high deployment and maintenance costs as well as poor environmental adaptability [6,7]. Especially in the early stage of leakage, the leakage of working fluid is small, and the signal change of conventional sensors is not obvious, which is prone to missed detection or response lag [8]. At the same time, the leakage diffusion path in a complex structural environment is significantly affected by local flow field and spatial occlusion, which makes it difficult for point monitoring methods to accurately reflect its spatial distribution characteristics [9]. Therefore, it is urgent to develop new monitoring methods that can achieve non-contact, large-scale, and high-sensitivity detection [10]. With the continuous development of optical measurement technologies, optical flow-field visualization has shown advantages such as high response speed, high sensitivity, strong anti-interference capability, high precision, and long detection distance, making it particularly suitable for pipeline leakage detection scenarios [11]. However, although traditional schlieren measurement can effectively visualize the morphology of gas jets, conventional optical measurement systems are often constrained by costly optical components and the difficulty of precise optical path alignment [12], which limits their application in large-scale equipment monitoring. In contrast, background-oriented schlieren (BOS) imaging technology overcomes such limitations and enables high-precision measurements [13,14]. In terms of image-based detection and flow-feature identification, Hu et al. [15] improved hybrid background-oriented schlieren tomography and demonstrated that reconstruction refinement can significantly enhance the fidelity of refractive-index-field recovery for quantitative diagnosis. Wu et al. [16] further showed that background-oriented schlieren can be extended from conventional flow visualization to the simultaneous characterization of multiple physical parameters in laminar flames. Cakir et al. [17] reported that optical-flow-based BOS provides reliable displacement estimation for compressible flows and offers clear advantages under conditions involving strong density gradients.

Recently, several main routes such as model-based analysis, signal-based sensing, and data-driven intelligent diagnosis have been proposed for high-pressure pipeline leak detection. Sekhavati et al. [18] systematically compared mass/volume balance, negative pressure wave, pressure point analysis, statistical methods, and real-time transient modeling, which showed that a single method often cannot achieve high detection speed, accurate localization, and reliable leak-size estimation at the same time. Yuan et al. [19] reviewed the applicability, performance limits, and engineering selection of existing leak detection and localization methods in oil and gas pipelines. Zhao et al. [20] further focused on pressure-wave-based approaches. They noted that these methods respond rapidly and suit long-distance pipelines, but their performance is still limited by wave attenuation, boundary reflection, and environmental noise under weak-leak and complex operating conditions. For specific detection approaches, acoustic and vibration sig-

nals remain major research directions in recent years. Ning et al. [21] developed a gas pipeline leak detection framework based on acoustic feature extraction, correlation analysis, and random forest. Their method improved recognition under strong background noise. Lin et al. [22] investigated buried natural gas pipeline leakage detection based on sound-source characteristics through both simulation and experiment, showing that acoustic-source features can be used to identify leakage under different aperture and pressure conditions. Dudić et al. [23] quantified compressed-air leakage on pipes using thermovision, demonstrating the potential of non-contact image-based thermal methods for leakage quantification in small-orifice cases. Wang et al. [24] numerically investigated the influence of gas dispersion on laser-based natural gas pipeline leakage detection, indicating that optical detection performance is strongly affected by leakage aperture, leakage velocity, and detection distance. These studies demonstrate that non-contact sensing and feature-based diagnostic indicators are promising for leakage monitoring; however, most existing methods still rely on single physical signals or static indicators, and the robustness of online decision-making under weak-leakage and complex-background conditions requires further improvement.

To improve robustness under complex conditions, recent studies have expanded toward unsupervised learning, multimodal fusion, and distributed fiber-optic sensing. Zhang et al. [25] proposed twin robust autoencoders for unsupervised leak detection in multivariate time series when normal operating data are corrupted. Zhan et al. [26] combined distributed acoustic sensing with a one-dimensional deep network for buried natural gas pipeline leak identification, demonstrating the potential of coupling distributed fiber optics with deep learning. Zhou et al. [27] introduced a lightweight method based on homologous multi-modal signal fusion, which improved both detection accuracy and deployment efficiency. Ma et al. [28] further fused distributed fiber-optic vibration and temperature signals for minor leak detection and localization. This line of work shows that current research is moving beyond simple binary recognition toward early detection, minor leak identification, and stable monitoring in complex environments.

Existing approaches to high-pressure pipeline leakage remain limited by slow manual response, distributed-sensor cost, and weak sensitivity to micro-leakage in complex installations. We therefore developed a BOS-based monitoring framework that reconstructs leakage-field density from background displacement and compresses the displacement field into one-dimensional features for template matching. Temporal smoothing and dual-threshold hysteresis stabilize the resulting alarm signal. Unlike CNN and other deep-learning detectors, the method requires no supervised training and uses only a compact reference library, reducing data preparation and supporting rapid site-specific deployment. Optical flow estimates general image motion, whereas the present workflow relates BOS displacement to leakage-oriented feature morphology. Conventional particle-image velocimetry requires tracer particles and controlled illumination, and optical gas imaging relies on gas-specific infrared absorption and dedicated hardware. The proposed framework therefore complements these methods as a comparatively simple and low-cost option for remote monitoring of colorless pipeline-gas releases.

2. Methodologies

2.1. Ground Test System and Experimental Condition Setup

Based on the principle of background-oriented schlieren (BOS) measurement, a micro-leakage detection experimental platform was constructed, as shown in Figure 1. The BOS imaging system employs a Nikon D7100 camera equipped with an adjustable-focus lens (30~105 mm). The background plate consists of a planar LED light source with an emitting area of 250×100 mm and an adjustable power range of 2~15.36 W. A random

dot background is fabricated using 0.3 mm diameter dots with a filling ratio of 50%. The leakage field simulation system is composed of a high-pressure gas source, pipelines, a high-frequency pressure sensor, and an ultrasonic flow sensor. Together, these components simulate a leakage field at the preset pressures, providing data support and verification capability for the leakage detection system.

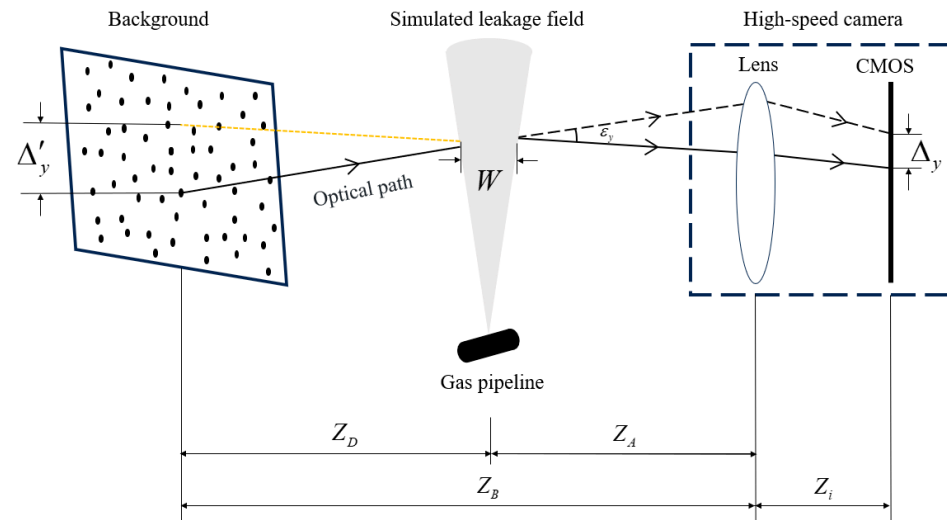


Figure 1. Background-oriented schlieren (BOS) measurement principle.

According to the sensitivity relationship of the BOS system, the optical configuration was set with $Z_D = 500$ mm, $Z_A = 100$ mm, and the camera focal length adjusted to 70 mm, and the aperture set to $f/8$. With the camera focused on the background plane at a distance of approximately 600 mm, the corresponding depth of field was approximately 20.7 mm. These high-sensitivity system parameters were selected to achieve a higher signal-to-noise ratio (SNR) in the experimental data. The same system configuration is further utilized for subsequent experimental validation of the leakage detection method. Considering the actual operating conditions of high-pressure pipelines in thermal power plants, a leakage orifice diameter of 0.5 mm was selected to characterize micro-leakage. Meanwhile, the leakage pressure ranged from 0.2 to 2.0 MPa, with an interval of 0.2 MPa. These settings ensure the acquisition of leakage-field datasets under standard operating conditions.

2.2. Image Processing Methods

The image processing procedure consists of two main components: cross-correlation calculation and density field reconstruction, as shown in Figure 2. Firstly, a cross-correlation calculation is performed between the reference image obtained under non-leakage conditions and the test image acquired under preset pressure leakage conditions. This calculation yields a displacement field, representing the spatial shift of light rays after passing through the region of interest and being captured by the imaging system. Based on the experimental configuration, the displacement information is then converted into deflection angles of light rays. Under the near-axis approximation, a Poisson equation is established in the least-squares sense to describe the refractive index distribution of the measured field. By solving the Poisson equation, the displacement field of the flow is reconstructed, which is subsequently converted into the density field using the Gladstone–Dale equation.

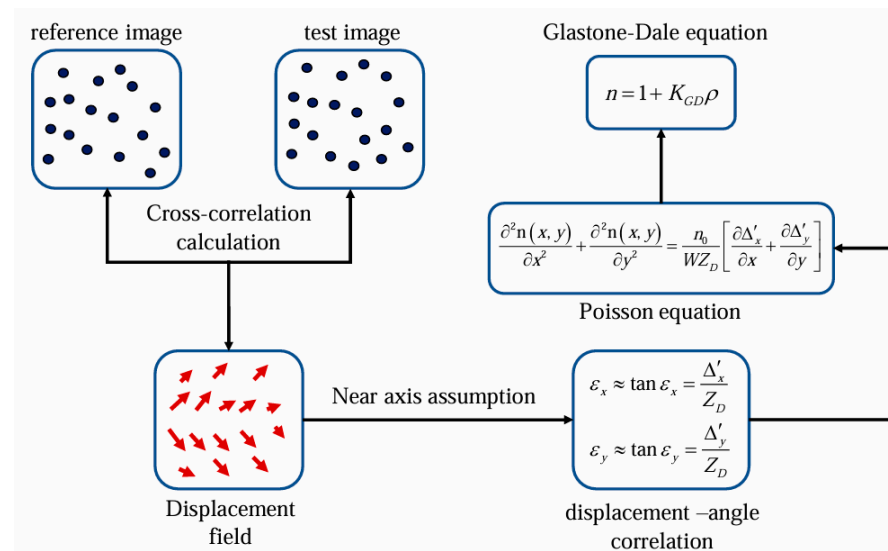


Figure 2. Processing workflow of background-oriented schlieren (BOS) images.

2.2.1. Cross-Correlation Calculation Method

In this study, the cross-correlation calculation was employed to perform a correlation calculation, and the principle diagram of this method is shown in Figure 3. The calculation is conducted between the reference image obtained under a non-leakage condition and the corresponding experimental image acquired under a specified pressure leakage condition. This process allows the extraction of the two-dimensional displacement field of the background pattern induced by the leakage-induced flow perturbation. For two two-dimensional images $f(x,y)$ and $g(x,y)$, the cross-correlation function can be expressed as shown in Equation (1).

$$R(x,y) = \iint f(m,n)g(m-\Delta x,n-\Delta y)dmdn \quad (1)$$

where $R(x,y)$ represents the matching degree between the two images at different relative displacements. The position corresponding to the correlation peak indicates the displacement variation within the local interrogation window. This method can robustly utilize the structural information of the background speckle pattern and is therefore more suitable for the measurement of small-scale displacements. Considering the refractive index magnitude of the measured field, the interrogation window size, search region, and overlap region were uniformly set to 36 pixels, 40 pixels, and 18 pixels, respectively, which achieved a balance between computational efficiency and spatial resolution.

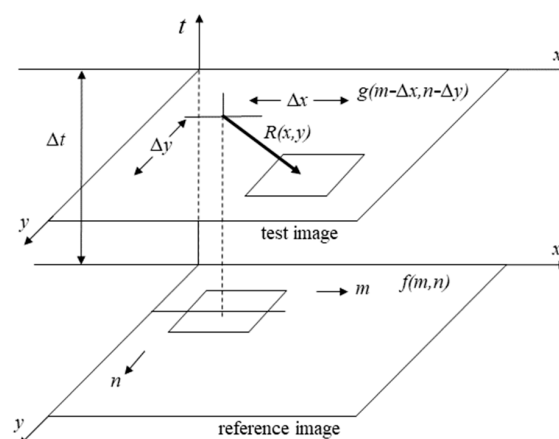


Figure 3. Schematic diagram of the cross-correlation calculation principle.

2.2.2. Method for Density Field Determination

After obtaining the displacement field, this study further establishes an inversion approach for reconstructing the refractive-index and density fields based on the theory of light-ray deflection. In background-oriented schlieren (BOS) measurements, the deflection angle of light rays can be approximately derived from the measured image displacement under the paraxial assumption, as shown in Equation (2)

$$\begin{aligned}\varepsilon_x &\approx \tan \varepsilon_x = \frac{\Delta'_x}{Z_D} \\ \varepsilon_y &\approx \tan \varepsilon_y = \frac{\Delta'_y}{Z_D}\end{aligned}\quad (2)$$

where ε_x and ε_y denote the deflection angles of light rays in the x and y directions, Δ'_x and Δ'_y represent the corresponding displacements of the background pattern in each direction, and Z_D is the distance between the test field and the background plate. The refractive index field can be obtained by jointly solving the two directional deflection equations in the least-squares sense, as expressed in Equation (3).

$$\frac{\partial^2 n(x,y)}{\partial x^2} + \frac{\partial^2 n(x,y)}{\partial y^2} = \frac{n_0}{WZ_D} \left[\frac{\partial \Delta'_x}{\partial x} + \frac{\partial \Delta'_y}{\partial y} \right] \quad (3)$$

where $n(x,y)$ denotes the refractive-index distribution within the field of interest, and the right-hand side of the Poisson equation represents the source term derived from the displacement-based deflection field. The equation is numerically solved using the finite-difference method (FDM) combined with Dirichlet boundary conditions, as shown in Figure 4, yielding the spatial distribution of refractive index for the test region. Based on the obtained refractive-index field, the density distribution can be further reconstructed according to the Gladstone–Dale relation, which provides a linear relationship between refractive index and fluid density, expressed as shown in Equation (4).

$$n = 1 + K_{GD}\rho \quad (4)$$

where n denotes the refractive index of the flow field, ρ represents the gas density, and K_{GD} is the Gladstone–Dale coefficient. Under fixed conditions of gas composition and measurement wavelength, K_{GD} can be regarded as a constant, which implies an approximately linear relationship between the refractive index and the density. It should be noted that, in the present single-view BOS configuration, the measured optical deflection contains the contribution of refractive-index gradients integrated along the optical line of sight [29]. Therefore, the refractive-index and density fields reconstructed using the two-dimensional Poisson equation should be interpreted as effective line-of-sight-projected fields rather than instantaneous local three-dimensional fields. The paraxial approximation is applied to the small optical deflection involved in BOS and does not imply that the flow itself is incompressible, laminar, or strictly two-dimensional. The Poisson equation is used to integrate the measured two-dimensional gradient information into a scalar refractive-index field, while the Dirichlet boundary condition is prescribed at the boundary of the region of interest where the leakage-induced disturbance approaches the ambient state. Under fixed gas composition and optical conditions, the Gladstone–Dale relation is subsequently used to convert the reconstructed refractive-index response into an effective density representation. Micro-leakage-induced disturbances that are difficult to identify directly in the original background-oriented schlieren images are effectively converted into the displacement field, refractive index distribution, and density field, enabling quantitative characterization of leakage behavior.

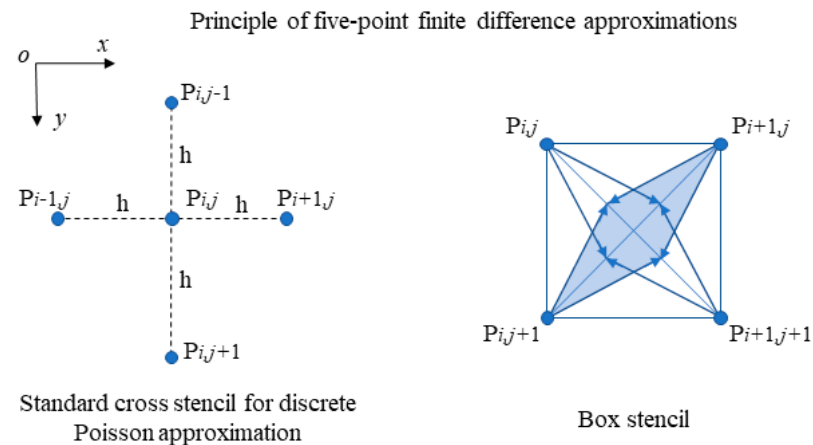


Figure 4. Schematic diagram of the finite-difference method (FDM) for refractive-index field reconstruction.

2.3. Feature-Based Leakage Monitoring Method

The monitoring pipeline first averaged successive BOS frames and estimated background displacement against a non-leakage reference by windowed cross-correlation. Each displacement field was then spatially compressed into a one-dimensional feature vector, retaining the dominant plume-scale morphology while reducing local fluctuations and computational dimensionality. The reference library was constructed exclusively from one complete database experiment and contained representative templates for predefined low-, intermediate-, and high-leakage regimes. Within each regime, feature vectors obtained using the same processing sequence were aggregated by their element-wise median, giving $T = \{t_{\text{low}}, t_{\text{mid}}, t_{\text{high}}\}$. For an incoming feature f , the monitoring score was defined as $s(f) = \max_k \text{NCC}(f, t_k)$, and the maximizing template supplied a coarse reference-morphology label. The score was subsequently processed by EMA smoothing and dual-threshold hysteresis.

For an ideal global illumination transformation $I' = aI + b$ ($a > 0$), zero-mean, unit-variance NCC is unchanged. NCC therefore reduces sensitivity to approximately uniform changes in brightness and feature amplitude when the background remains visible and correctly exposed. Frame averaging, spatial compression, and EMA smoothing further attenuate local, isolated, and short-lived fluctuations before the smoothed score is converted into an alarm state. The alarm is activated at $\tau_{\text{on}} = 0.650$ and retained until the score falls below $\tau_{\text{off}} = 0.600$, limiting repeated switching within the hysteresis band. In the independent sequence, upper thresholds from 0.60 to 0.75 produced no false-alarm frames and two state transitions, with leakage-frame alarm coverage from 0.919 to 0.959. The selected 0.650/0.600 pair achieved 0.932 coverage with no false-alarm frames and two transitions. For the fixed half-scale region of interest, the monitoring algorithm updated the alarm state in approximately 0.1 s per sampled point.

2.4. Independent Evaluation Protocol

The reference library and evaluation samples were obtained from two separately acquired complete experiments stored as independent video and pressure-data files. The database experiment was used only for feature extraction and template construction, whereas the second experiment served as the independent test sequence. It was excluded from regime definition, template selection and aggregation, library updating, and result adjustment. The experiments used different pressure programs and optical placement coordinates while retaining the principal imaging settings, so temporally adjacent frames from one experiment were never divided between the library and test set. Performance on

the fixed independent sequence was summarized by ROC and precision–recall curves, AUC, AP, and the reported composite evaluation score at the engineering threshold. Threshold sensitivity was assessed using leakage-frame alarm coverage, non-leakage false-alarm rate, and alarm-state transitions.

3. Result and Discussion

3.1. Image Processing Method Verification and Analysis

The 1.2 MPa condition was selected as a representative intermediate-pressure case to verify the effectiveness of the background-oriented schlieren (BOS) method in the visualization and quantitative analysis of leakage flow fields. Under this condition, the leakage jet is sufficiently developed, and three distinct Mach-disk-related jet structures can be clearly identified, providing representative flow-field features for evaluating the reconstruction capability of the proposed method. Cross-correlation displacement extraction, refractive-index field reconstruction, and density-field calculation were then performed sequentially, and the results obtained at each stage were compared and analyzed, as shown in Figure 5. The jet boundary can be clearly observed in the displacement vector field obtained from the cross-correlation calculation, which is difficult to discern in the raw experimental images, while the internal structure remains difficult to observe. After further inversion based on the Poisson equation and the Gladstone–Dale relation, the reconstructed refractive-index and density fields reveal detailed internal flow structures, well-defined jet boundaries, and surrounding plume regions, as shown in Figure 5. These findings demonstrate that the proposed BOS-based image-processing method enables effective visualization and characterization of micro-leakage flows.

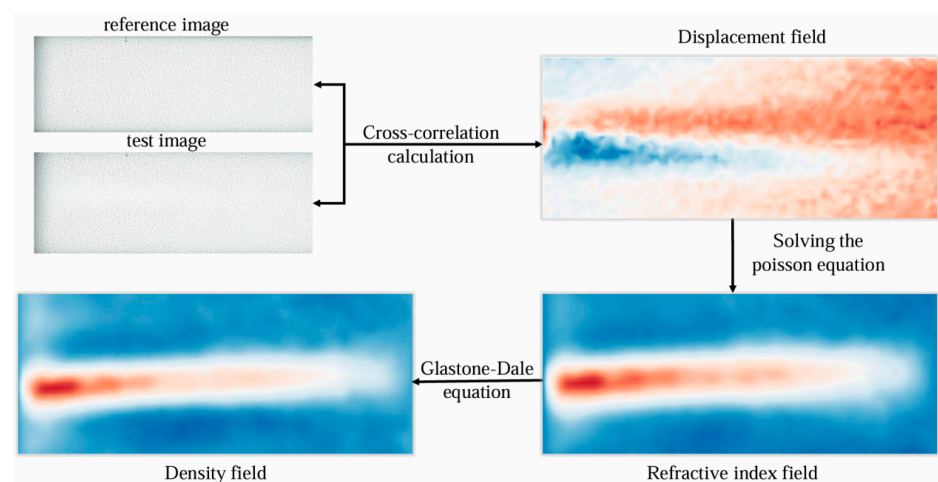


Figure 5. Verification of the image-processing method.

Furthermore, the density field distribution obtained under the operating condition of 1.2 MPa was compared with the corresponding result from numerical simulations, which were conducted using the commercial software Fluent (2022 R2). Since the main jet region exhibited an approximately steady-state flow, the RANS model was employed to perform a steady-state solution for a two-dimensional axisymmetric model with a leak orifice diameter of 0.5 mm. To quantitatively evaluate the reconstruction results, three transverse data-acquisition lines were arranged at 5, 10, and 15 mm downstream of the leakage orifice. As observed from the reconstructed flow structure in Figure 5, the three sampling locations at 5, 10, and 15 mm correspond closely to the three characteristic Mach-disk-related high-density regions under the 1.2 MPa condition. Therefore, these sampling lines pass through representative characteristic regions of the developed jet, enabling the density distributions at different downstream stages to be compared effectively. Each line extended 2.5 mm above and below the jet axis and

contained 100 data points. The density profiles extracted from the BOS measurements and numerical simulations were then compared, as shown in Figure 6.

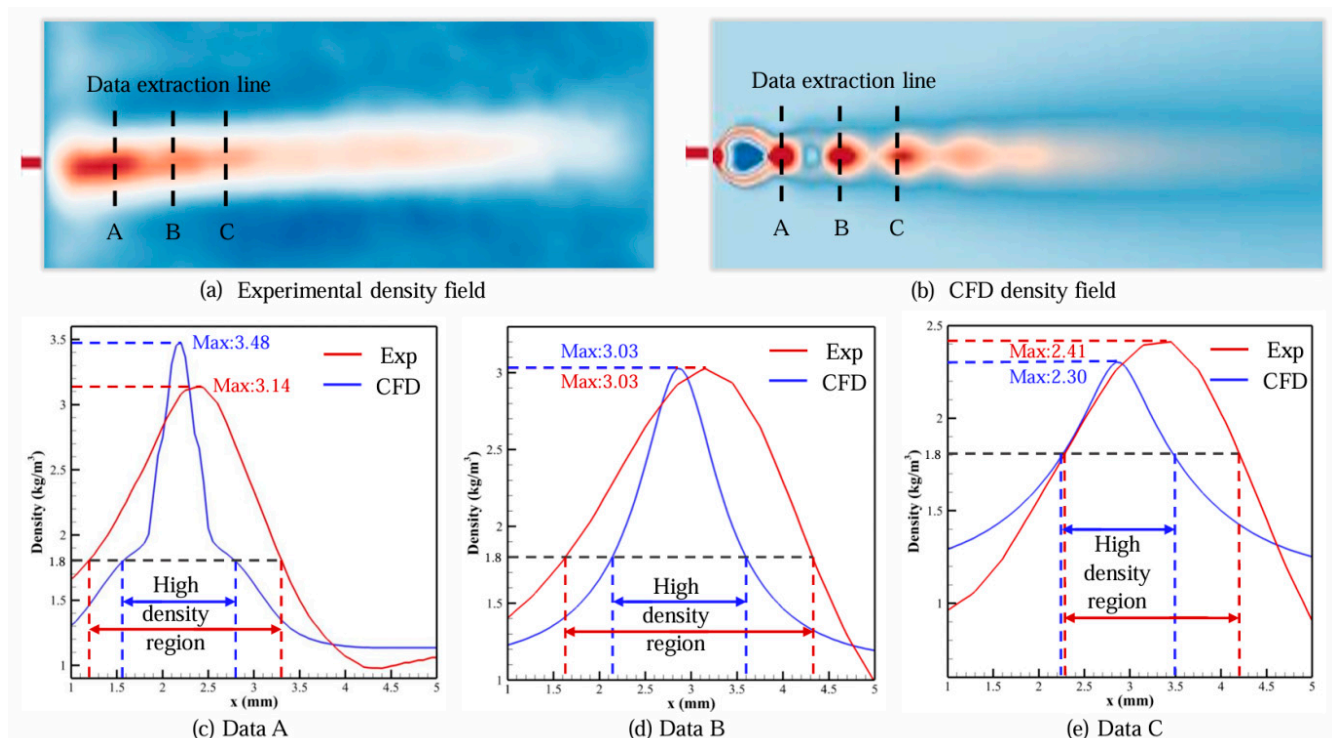


Figure 6. Comparison between experimental density field and numerical simulation results.

Firstly, the extracted density data were subjected to a comparison of their peak density values, which determines whether accurate recognition of different pressure levels can be achieved after subsequent one-dimensional compression for graded alarm classification. As shown in Figure 6, the density peak errors of the three sampling datasets were 9.8%, 0%, and 3.7%, indicating that, under the representative 1.2 MPa condition, the BOS reconstruction effectively reproduces the dominant density response in the high-density regions of the leakage jet. This result provides quantitative support for the retention of the dominant leakage characteristics required for subsequent feature extraction and graded identification.

Subsequently, A density value exceeding 50% of the density under normal temperature and pressure conditions was defined as the detectable high-density threshold, which is 1.8 kg/m^3 . The widths of the detectable high-density regions obtained from the three sampling datasets were then compared. The width errors of the identifiable high-density regions were 38.1%, 42.3%, and 38.9%, indicating certain deviations from the numerical simulation results. These deviations mainly reflect the limited spatial accuracy in recovering the jet boundary and should be distinguished from the reconstruction of the dominant density response in the jet core. In single-view BOS measurements, the optical deflection contains refractive-index-gradient information integrated along the line of sight [29]. In addition, the finite interrogation window used in the cross-correlation calculation introduces spatial averaging, and previous studies have shown that a sharp density variation can be recovered as a gradual displacement transition whose spatial extent is affected by the interrogation-window size [30]. Finite depth of field and geometric defocus blur can further smooth localized BOS signals and broaden the resulting spatial profile [31]. Consequently, the experimentally reconstructed jet boundary becomes smoother than the relatively sharp boundary in the local CFD density field. When a fixed density threshold is used to identify the boundary, this spatial smoothing can lead to an apparent broadening of the identified high-density region. Therefore, the threshold-defined width is considered

here as a semi-quantitative indicator of the spatial extent of the detectable leakage region rather than as a high-accuracy measurement of the physical jet boundary.

The above comparison provides a detailed quantitative evaluation of the reconstructed density distribution under the representative 1.2 MPa condition. However, because the spatial structure, extent, and locations of the high-density regions of the leakage jet vary with pressure, the fixed transverse sampling positions of 5, 10, and 15 mm used in Figure 6 do not necessarily correspond to equivalent high-density regions under all pressure conditions. Directly applying the same transverse sampling locations over the complete pressure range may therefore introduce additional differences associated with the pressure-dependent evolution of the jet structure.

To further evaluate whether the dominant density response can be consistently reproduced over the complete pressure range, the density distribution was extracted along the jet centerline for each pressure condition, and the maximum value along the centerline was taken as the representative peak density. This approach avoids the dependence on fixed transverse sampling locations that may not intersect the corresponding high-density regions as the jet structure changes with pressure. The peak densities obtained from the BOS reconstruction and numerical simulation over 0.2–2.0 MPa are compared in Figure 7. The experimental statistics were obtained from two independently acquired pressure-test datasets, with 20 valid samples randomly selected from the corresponding steady interval at each pressure step. The mean centerline peak density was calculated for each pressure level; the error bars represent ± 1 standard deviation (SD), while the dashed upper and lower bounds and the shaded band indicate the 95% confidence interval (CI) of the mean.

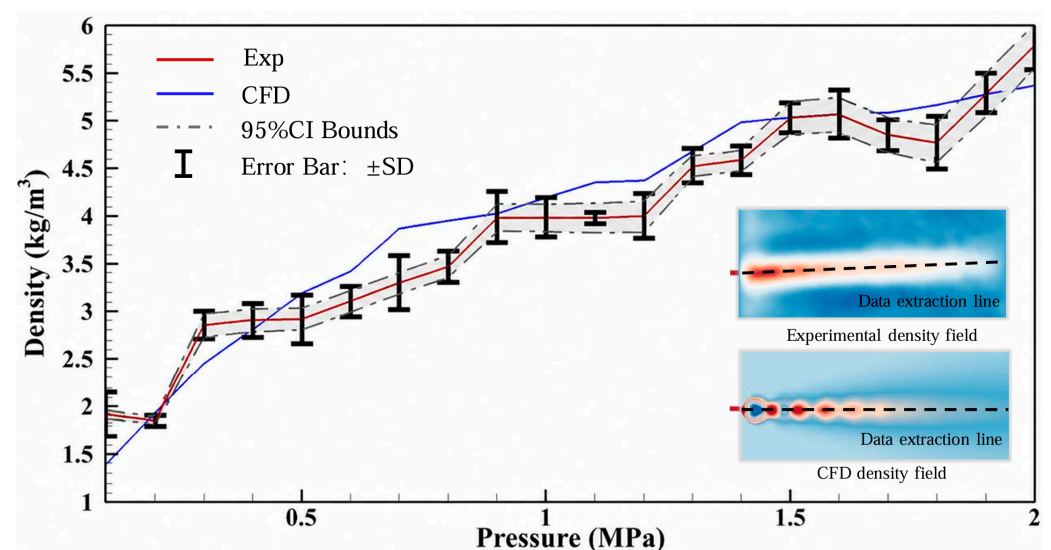


Figure 7. Comparison of centerline peak densities obtained from BOS reconstruction and numerical simulation under different leakage pressures.

As shown in Figure 7, the mean experimental peak densities obtained from the BOS reconstruction and numerical simulation exhibit highly consistent pressure-dependent trends over the range of 0.2–2.0 MPa. With increasing leakage pressure, both results reproduce the same overall evolution of the dominant density response. The standard-deviation error bars and 95% confidence intervals further characterize the dispersion and statistical uncertainty of the experimental peak-density measurements at each pressure level. The maximum absolute deviation between the experimental mean values and the numerical simulation results is 0.5688 kg/m^3 . Although local quantitative differences remain, the BOS reconstruction effectively reproduces the pressure-dependent variation of the dominant peak-density response. This additional comparison extends the validation

from the detailed local density-profile comparison at the representative 1.2 MPa condition to the evaluation of the dominant density response over the complete pressure range.

In summary, the representative 1.2 MPa condition provides a detailed evaluation of the reconstructed density profiles at different downstream locations, while the additional centerline peak-density comparison extends the evaluation of the dominant leakage response to the full pressure range of 0.2–2.0 MPa. The consistent pressure-dependent trends obtained from the BOS reconstruction and numerical simulation demonstrate that the proposed method can effectively reproduce the evolution of the dominant density response with leakage pressure. In contrast, the threshold-defined jet width is subject to larger spatial uncertainty because of the line-of-sight projection and spatial-smoothing effects discussed above. It should be emphasized that the fixed-threshold width is not used as the direct decision variable in the subsequent leakage-identification framework. The subsequent identification is based on the complete one-dimensional feature curve extracted from the displacement-amplitude field, in which the dominant leakage-core response is retained together with its spatial structural and attenuation characteristics. Therefore, the full-pressure-range peak-density comparison provides complementary quantitative evidence that the principal leakage response relevant to subsequent feature identification can be consistently captured under different pressure conditions.

3.2. Data Comparison and Feature Extraction of Image-Processing Results

Under different leakage-pressure conditions, the flow-field structure exhibits distinct variations. To further evaluate the responsiveness of the proposed background-oriented schlieren (BOS)-based processing method to operating-condition changes, the density-field distributions obtained under various pressures were compared, as shown in Figure 8. The contour plots are normalized with respect to the maximum density value of 5.8 kg/m^3 measured at 2.0 MPa.

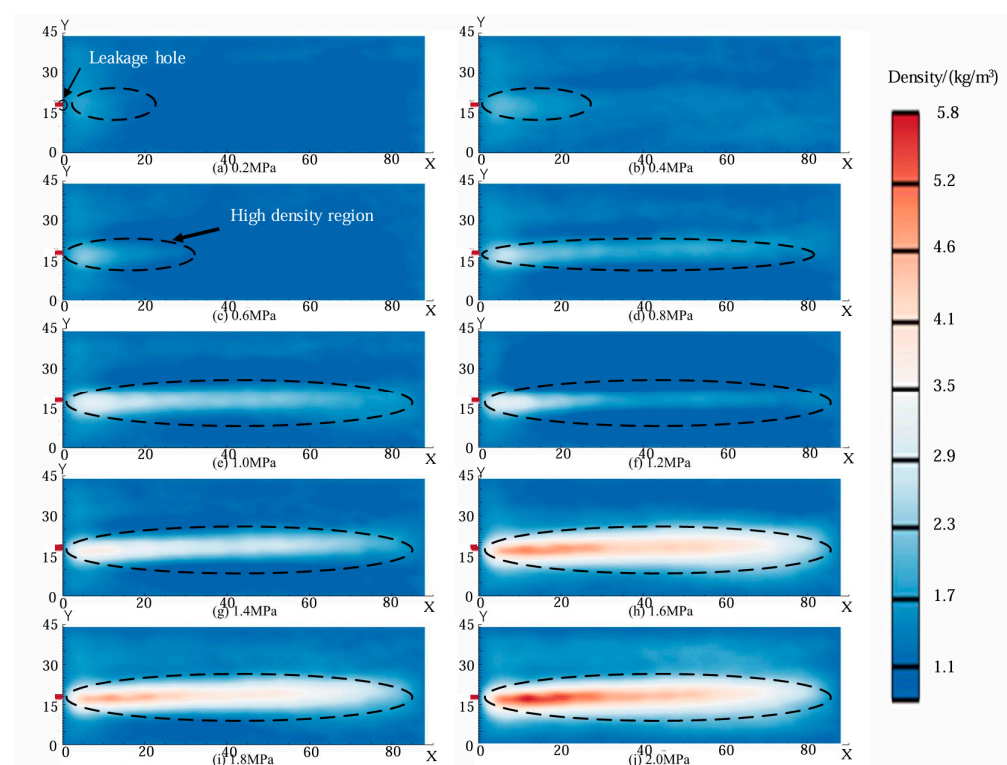


Figure 8. Density contour maps obtained from experiments.

As shown in Figure 8, within the low-pressure range of 0.2~0.8 MPa, the jet-boundary region continuously expands with increasing pressure, while both the main-flow core and peripheral plume structure become progressively clearer. Local areas of high density gradients are more pronounced, which are defined here as the area expansion region. In the higher-pressure range of 1.0~2.0 MPa, the jet boundary remains relatively constant in size, but the central density gradually increases, and the boundary gradient becomes sharper, corresponding to the density enhancement region. Considering both jet area and core density evolution, the density-contour plots demonstrate a distinct pressure-dependent change in flow-structure characteristics. These results verify that the proposed BOS-based method can stably and effectively respond to variations in leakage pressure, exhibiting strong repeatability and reliability in quantitative flow visualization.

Furthermore, to quantitatively analyze the variation of density distribution under different pressure conditions, density values exceeding 50% of the ambient air density were defined as identifiable high-density feature points. The number of such points was extracted from the experimental density-field data, as shown in Figure 9. In the pressure range of 0.2~0.8 MPa, which is the area of expansion defined in this paper, the number of high-density feature points increases significantly with the increase of pressure, and maintains a high growth rate before 0.8 MPa. In the pressure range of 1.0~2.0 MPa, in the density enhancement zone, the number of high-density feature points continues to increase, but its growth rate is significantly reduced. This change trend further verifies the above analysis results: in the area growth stage, the spatial expansion of the main jet area dominates the flow field changes; while in the density growth stage, the jet size is basically stable, and the main changes are reflected in the gradual enhancement of the density of the core area.

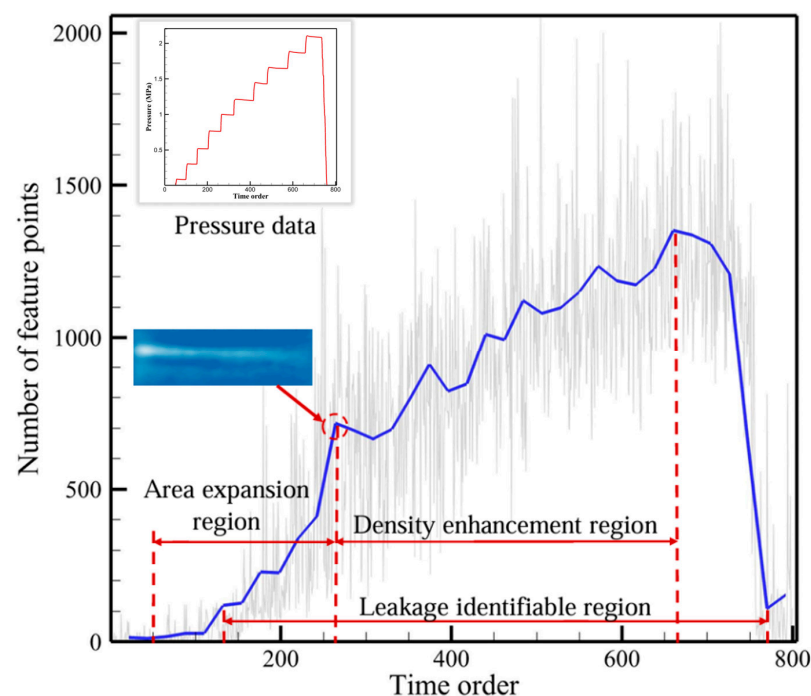


Figure 9. Density-field data extraction from experimental results.

According to the experimental results under different leakage pressure conditions, it can be seen that the image processing and feature extraction methods proposed in this paper can respond stably to changes in pressure. At the same time, there is a strong correlation between the number of high-density feature points that can be identified in the density field and the actual leakage pressure. With the increase in leakage pressure,

the structural characteristics of the jet area gradually become obvious, and the clarity and recognition of the extracted results also improve. These results show that the method has good adaptability and expansion ability under different working conditions, providing a solid experimental basis for the subsequent research on feature-based state identification and online micro-leakage detection.

3.3. Feature Recognition Results

The BOS displacement fields were compressed into one-dimensional features and evaluated against the fixed three-template library using the processing sequence shown in Figure 10. Across the evaluated sequence, the compressed representation retained the dominant plume-scale structure while reducing isolated local variation. Template matching produced a continuous NCC score and a coarse morphological label governed mainly by relative feature shape rather than absolute amplitude. EMA smoothing preserved the sustained increase during leakage while reducing short-lived score excursions. The 0.650/0.600 hysteresis pair then converted the smoothed score into a stable state sequence with two transitions, no false-alarm frames, and leakage-frame alarm coverage of 0.932 in the independent test.

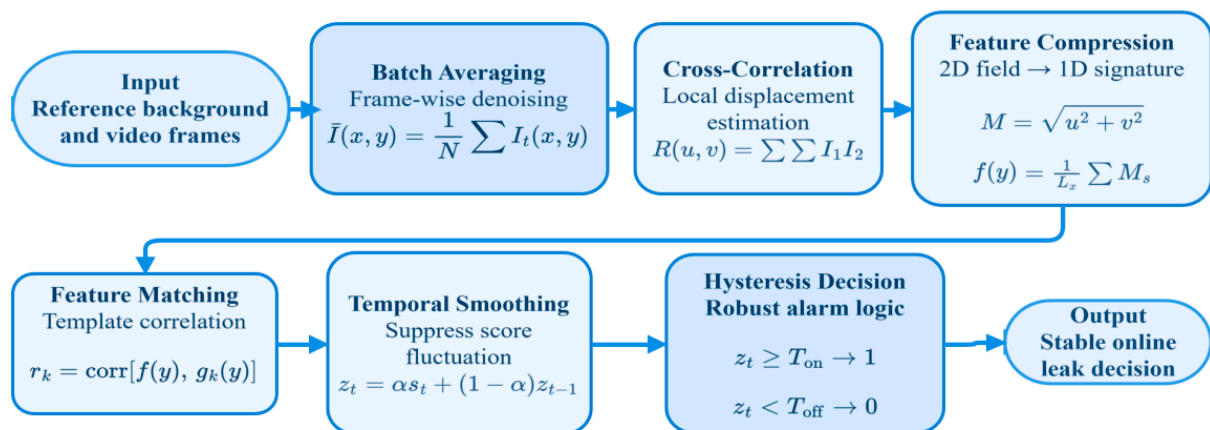


Figure 10. Workflow of online micro-leakage detection.

As shown in Figure 11, the extracted one-dimensional feature curves are not merely numerical signals generated by statistical compression, but compact representations of the spatial structure of the leakage-induced displacement field. The dominant peak corresponds to the main plume core, where the displacement response is strongest because of optical deflection induced by a pronounced density gradient. The downstream attenuation section and its adjacent shoulder region reflect the transition process from the core disturbance zone to the surrounding environmental fluid. The low-amplitude outer segment corresponds to the weak-disturbance background region. The principal extrema and decay characteristics of the feature curve establish an interpretable link between the low-dimensional signal and the underlying leakage-flow structure.

Compared with the reference curve, the leakage characteristic curve not only shows a stronger response amplitude, but also shows obvious structural differences in peak occurrence, peak width, attenuation behavior, and valley distribution. In contrast, the baseline curve is relatively flat overall, and no organized response patterns related to the core area or transition area of the plume have been observed. This comparison shows that based on the characteristic characterization method proposed in this paper, leakage-induced disturbances can be distinguished from background fluctuations at the structural level, not just by relying on local amplitude surge. This characteristic is of great practical significance because it provides a basis for subsequent correlation-based feature library matching

and makes the leakage alarm process have clear physical significance and engineering operability at the same time.

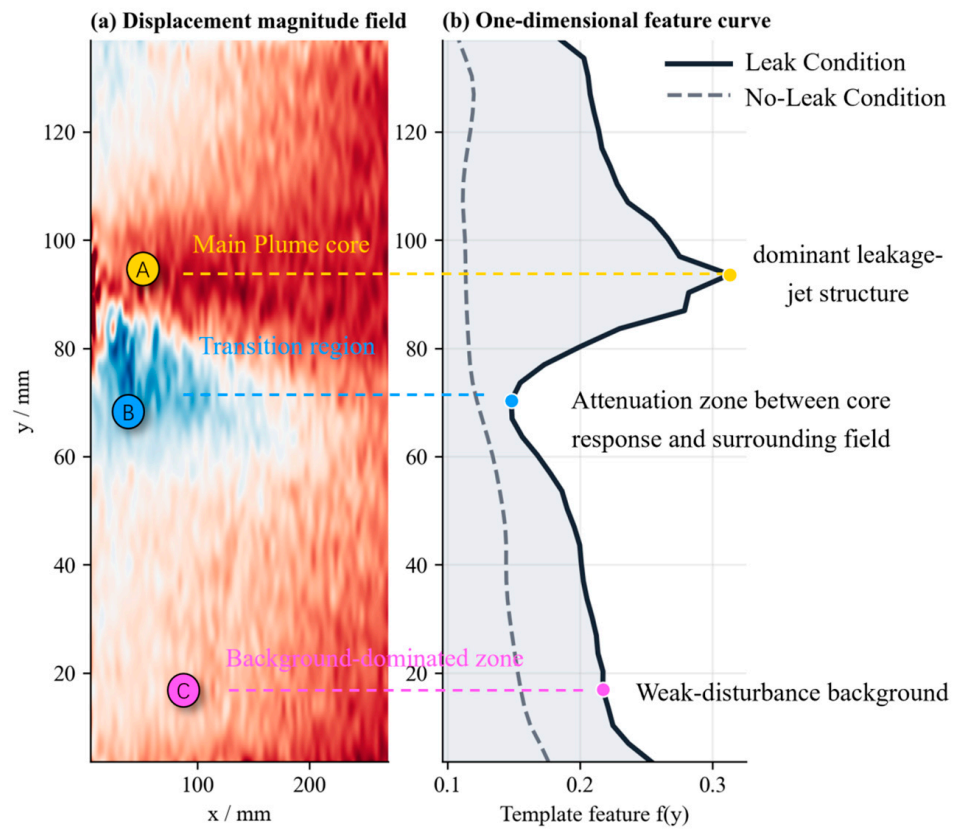


Figure 11. Physically interpretable feature curves under leakage and baseline conditions.

Together, the separation between leakage and baseline features shows that the compressed representation retained physically interpretable information for state discrimination. NCC matching and temporal regularization converted this separation into an alarm-oriented output under the tested optical arrangement.

3.4. Detection Performance and Decision Stability

To test whether the fixed representation transferred beyond the database experiment, the feature library was applied without updating to the separately acquired independent sequence. The analysis evaluated discrimination, threshold sensitivity, temporal stability, and coarse state matching.

As shown in Figure 12, on the independent sequence, ROC analysis yielded an AUC of 0.992, precision–recall analysis yielded an AP of 0.998, and the reported composite evaluation score was 0.972 at $\tau_{\text{on}} = 0.650$. Because no test frame contributed to template construction, library updating, or result adjustment, these metrics quantify transfer from the database experiment to the separately acquired sequence. The Youden threshold was 0.618, while 0.650 and 0.600 were retained as the engineering activation and release thresholds. As summarized in Table 1, upper thresholds from 0.60 to 0.75 produced no false-alarm frames and two state transitions; the selected pair yielded leakage-frame alarm coverage of 0.932. Lowering the pair to 0.550/0.500 increased coverage to 0.973 but introduced a false-alarm rate of 0.182 and reduced the transitions to one. Raising it to 0.9145/0.8645 reduced coverage to 0.851 without improving false alarms or transitions. The selected pair therefore represents a stable operating point for the present configuration.

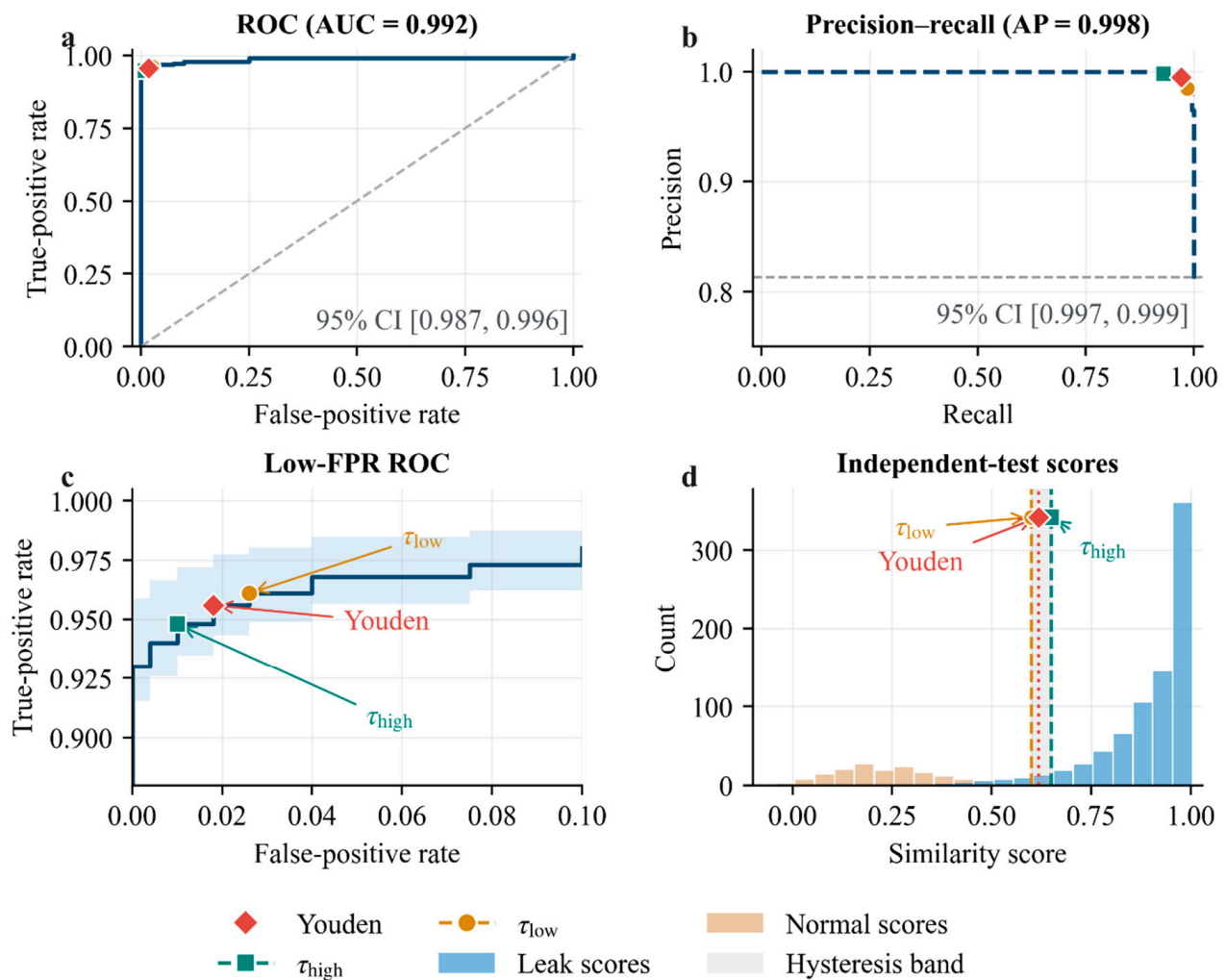


Figure 12. Performance evaluation of the proposed leak detection method on the independent test set. (a) Receiver operating characteristic (ROC) curve. (b) Precision–recall (PR) curve. (c) Enlarged low-false-positive-rate (Low-FPR) region of the ROC curve showing the optimal Youden threshold and the hysteresis thresholds. (d) Similarity-score distributions for normal and leakage samples, illustrating the locations of the Youden threshold and the hysteresis thresholds used for alarm activation and release.

Table 1. Threshold-sensitivity analysis for the dual-threshold hysteresis monitor.

Upper/Lower Threshold	Leakage-Frame Alarm Coverage	Non-Leakage False-Alarm Rate	Alarm-State Transitions
0.550/0.500	0.973	0.182	1
0.600/0.550	0.959	0.000	2
0.650/0.600	0.932	0.000	2
0.700/0.650	0.919	0.000	2
0.750/0.700	0.919	0.000	2
0.9145/0.8645	0.851	0.000	2

Figure 13 shows the raw score, EMA-smoothed score, and hysteresis state for the independent sequence. Smoothing attenuated short-lived excursions, while hysteresis prevented immediate state reversal within the threshold band. The alarm was activated after the smoothed score exceeded 0.650 and released only after it fell below 0.600, maintaining continuous monitoring across the observed short fluctuations.

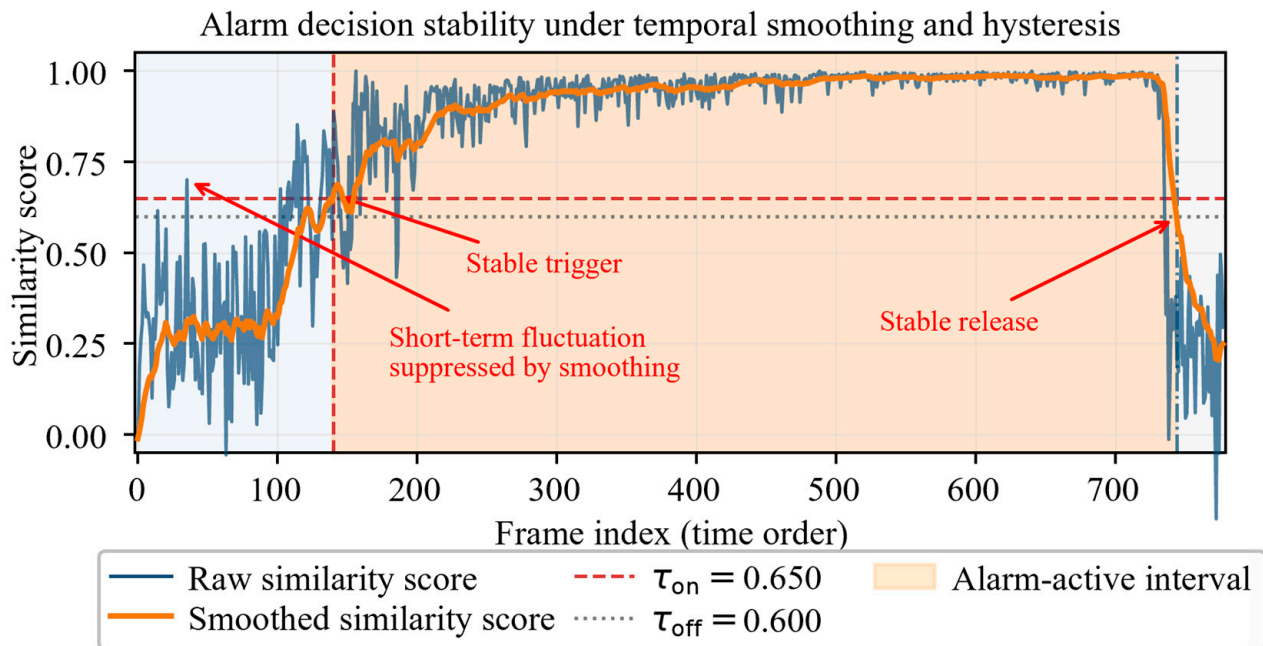


Figure 13. Time-series alarm response based on the dual-threshold hysteresis strategy.

Figure 14 shows the best-matching trajectory among the low-, intermediate-, and high-regime templates. Persistent assignment indicates similarity to the corresponding reference morphology, whereas switching near a transition reflects ambiguity between coarse regimes. Temporal smoothing produced a more continuous dominant match, supporting the use of the one-dimensional features for coarse state discrimination. Together with the ROC, threshold-sensitivity, and time-series results, this trajectory supports statistical discrimination, temporally stabilized alarms, and coarse three-regime matching under the tested conditions. Because the library is specific to the present optical arrangement, additional complete experiments are needed to quantify template stability and transferability.

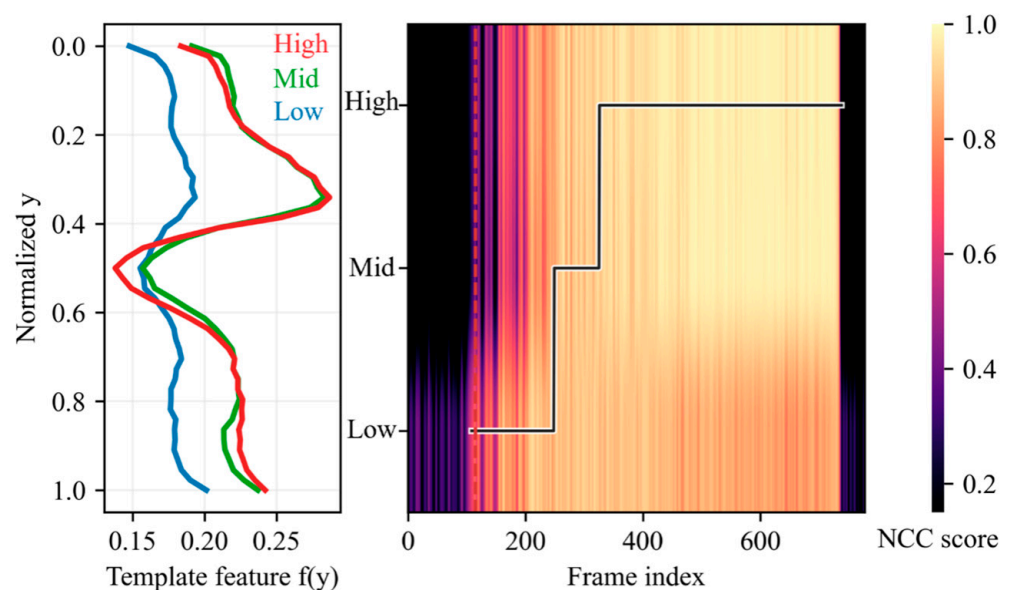


Figure 14. Correlation heatmap of multi-feature matching.

3.5. Monitoring Applicability and Limitations

To further evaluate the robustness of the monitoring method against short-duration image disturbances, its response was examined during stable non-alarm and alarm periods,

as shown in Figure 15. Two representative forms of interference were introduced while all monitoring parameters were kept unchanged. Short-term random intensity fluctuations were used to represent sensor-level image noise, whereas localized transient displacement of the background texture was introduced to represent limited background motion. Both disturbances affected the instantaneous NCC score, but neither altered the alarm state within the tested range. During the non-alarm period, random intensity fluctuations produced maximum changes of 0.188 in the raw score and 0.028 in the smoothed score. Local background motion resulted in corresponding changes of 0.327 and 0.026, respectively. During the alarm period, the effects were smaller: the maximum changes in the raw and smoothed scores were 0.00193 and 0.000154 for intensity fluctuations, and 0.0730 and 0.00584 for background motion, respectively. In all four tests, the original alarm sequence and transition points remained unchanged.

Sensitivity to short image perturbations in non-alarm and alarm regions

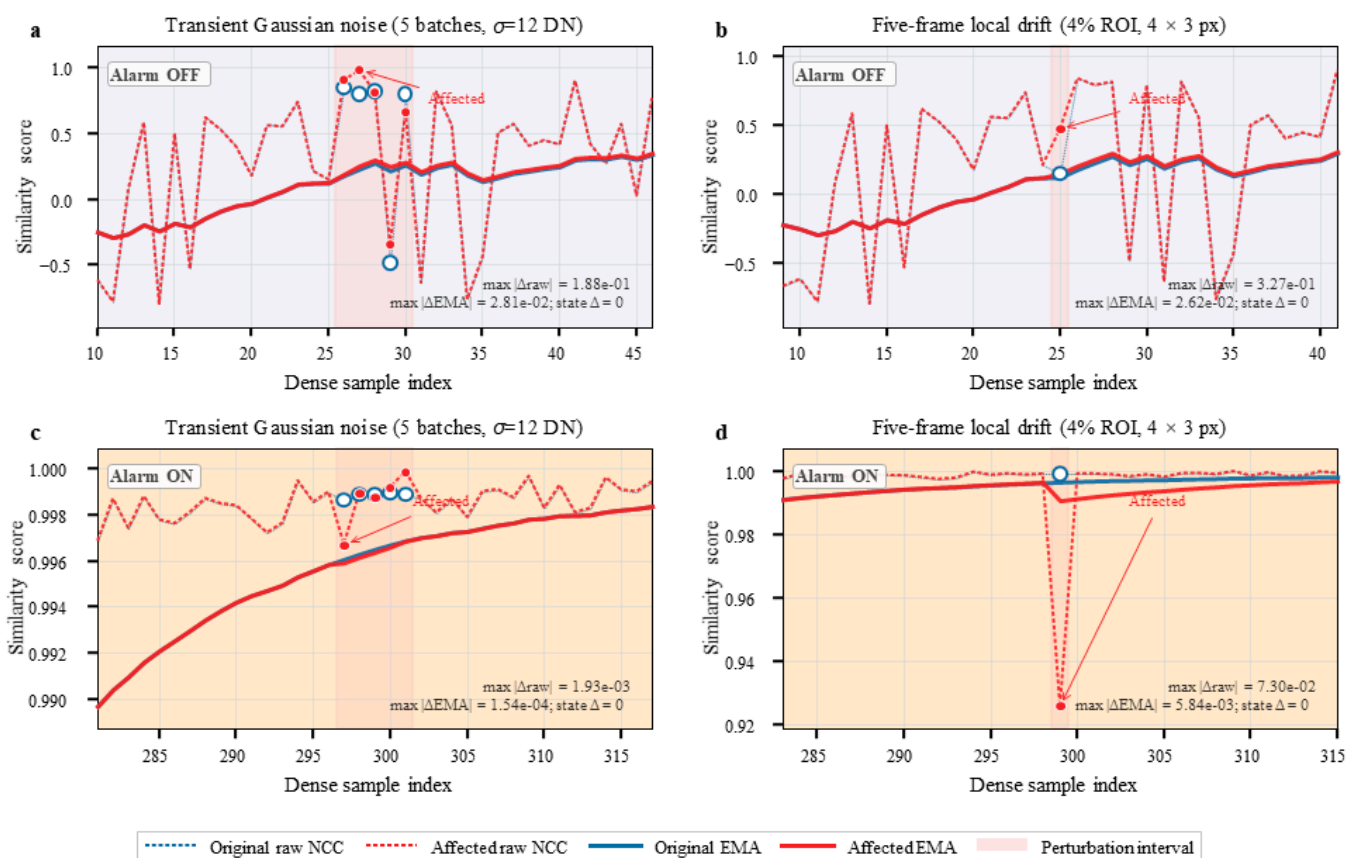


Figure 15. Stability of the monitoring decision under bounded short-duration image disturbances. Transient random intensity fluctuations were introduced in the non-alarm (a) and alarm (c) regions, whereas localized background motion was introduced in the non-alarm (b) and alarm (d) regions. Blue curves and open circles show the original results; red curves and filled circles show the affected results. Shaded areas indicate the disturbance intervals.

The observed decision stability results from the combined effects of several stages in the monitoring process, each of which serves a distinct function. Normalized NCC reduces sensitivity to approximately uniform variations in image brightness. Frame averaging attenuates short-duration fluctuations, while spatial compression of the displacement field limits the influence of disturbances confined to a small local region. EMA smoothing further suppresses isolated score variations from dominating the recent temporal response, and the hysteresis mechanism preserves the current alarm state until the opposite threshold

is crossed. Together, these operations explain why the tested disturbances altered the similarity score without changing the final monitoring decision. However, these mechanisms do not eliminate physical interference itself, nor do the present tests establish robustness under arbitrary disturbance conditions.

BOS monitoring still requires a visible and sufficiently contrasted background together with a stable optical arrangement. Under prolonged or severe interference, the background texture may no longer remain reliably identifiable. Such conditions may arise from severe non-uniform illumination, saturation, pronounced defocus, sustained camera motion, large-scale background movement, or dense dust, which may weaken or distort the correlation peak. These conditions exceed the disturbance range evaluated in Figure 15 and therefore require renewed calibration and dedicated validation. A substantial change in the installation configuration also requires the reference image and template library to be reconstructed using local data, while the decision thresholds and smoothing parameters should be re-evaluated under the new conditions. In addition, monitoring distance and pipe geometry affect image resolution and BOS sensitivity, gas composition influences the optical response, and extreme pressure conditions may generate apparent displacements beyond the reliable range of the present correlation analysis.

4. Conclusions

This study proposes a high-pressure pipeline micro-leakage detection method based on background-oriented schlieren (BOS) measurement and feature matching. An integrated procedure from flow field measurement to micro-leakage detection is established by combining BOS-based visualization of the leakage flow field, one-dimensional compression of displacement field features, and feature matching for leakage detection. The main conclusions are as follows:

1. The density distribution of the leakage field was reconstructed based on the background-oriented schlieren (BOS) technique, with the density peak error relative to the numerical simulation results maintained within 10%. Micro-leakage disturbances that are difficult to distinguish in raw images were accurately transformed into two-dimensional data representations with clear physical significance.
2. Based on the density-field images from background-oriented schlieren (BOS), the transition of the dominant leakage characteristic from an area expansion region to a density enhancement region under different leakage pressures was revealed. On this basis, the displacement field was further compressed into a one-dimensional representation, and normalized-correlation-based matching, temporal smoothing, and dual-threshold hysteresis decision-making were introduced, thereby achieving stable detection of the micro-leakage field.
3. Applying the fixed feature library to a separately acquired complete test experiment yielded an AUC of 0.992, an AP of 0.998, and a reported composite evaluation score of 0.972 at $\tau_{\text{on}} = 0.650$. These results support leakage-state monitoring and coarse three-regime matching under the tested conditions. Quantitative inversion of pressure, temperature, or leakage intensity requires separate calibration and additional thermodynamic information.

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