Advances in Engineering Research : Possibilities and Challenges
ISSN Print: 3079-5192
ISSN Online: 3079-5206
https://doi.org/10.63313/AERpc.9071

An Elliptical Envelope-Based Method for Casing Corrosion Diagnosis

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How to cite this paper: Li, G. A. (2026). An Elliptical Envelope-Based Method for Casing Corrosion Diagnosis. *Advances in Engineering Research: Possibilities and Challenges*, 3(2), 43-49. ISSN Print: 3079-5192; ISSN Online: 3079-5206.
https://doi.org/10.63313/AERpc.9071
Published: 2026-01-19

Abstract

Casing corrosion leading to wall thinning or perforation poses a major threat to wellbore integrity, highlighting the urgent need for accurate corrosion diagnosis technology. To address this, this study proposes a casing corrosion diagnosis method based on the EllipticEnvelope anomaly detection algorithm. Utilizing well logging data, the method establishes a robust covariance estimation model via the EllipticEnvelope algorithm to effectively identify corrosion-related anomalies. Taking the data from Well XX in the Ordos Basin as an example, the proposed method achieved a detection accuracy of 92.3%. Compared to the Isolation Forest and threshold methods, this represents an improvement of 12.42% and 31.48%, respectively. The results demonstrate that the method can identify casing corrosion more effectively, providing a reliable technical means for downhole condition assessment.

Keywords

EE; Outlier Detection; Feature Extraction; Casing Corrosion Diagnosis

1. Introduction

Corrosion of wellbore casings poses a significant threat to the safety of oil and gas production operations. Corrosion-induced pipe wall thinning or perforation can result in severe incidents such as blowouts and leaks, leading to substantial economic losses and environmental harm [1].In submarine pipelines, corrosion is a primary factor contributing to buckling and leaks, with its detrimental impact escalating with increasing water depth and pressure [2]. Studies indicate that 40% of oil and gas well workover instances are attributed to corrosion-related damage, with individual replacement costs reaching millions of dollars [3]. The spatial clustering of corrosion defects further elevates the risk of leaks [4]. Hence, the development of efficient and precise corrosion diagnostic technologies is imperative to safeguard wellbore integrity.

Conventional corrosion detection methods exhibit limitations. Physical inspection approaches, like X-ray backscatter radiography, are suitable for one-sided inspection scenarios but face challenges in optimizing photon energy and detector positioning, making it challenging to balance efficiency and accuracy [5]. Guided wave tomography (GWT) can assess wall thickness loss in curved pipes, yet it may incur a depth estimation error of 3%-8% for irregular corrosion profiles [6]. Non-destructive inspection using ground penetrating radar (GPR) relies on amplitude attenuation analysis, which proves inadequate for early detection of hidden corrosion [7]. In intricate marine settings, such as fluid corrosion in jumper pipes under high temperature and pressure, conventional methods struggle to detect small cracks (< 0.2 mm) [8]. Moreover, the presence of high temperature, high pressure, and multiphase flow in downhole environments further hinders sensor deployment and real-time monitoring efficacy [9-10].

Based on this, we propose an outlier detection model centered on the EllipticEnvelope (EE) algorithm. The EE algorithm is employed to estimate the robust covariance of multidimensional logging parameters, effectively modeling the elliptical distribution domain of corrosion-related features for the identification of anomalies. This approach leverages the spatial clustering capability of the elliptical envelope method to detect abnormal patterns indicative of corrosion. The efficacy of the proposed EE-based method is validated using casing corrosion data from an oilfield. Its performance is compared against conventional threshold-based and other single-model testing approaches, presenting a focused and intelligent diagnostic framework for evaluating downhole string integrity.

2. Corrosion Characteristics

Geometrical and statistical features pertaining to corrosion are derived from logging data to define various types of corrosion, as illustrated in **Figure 1** Perforation denotes severe localized corrosion resulting in a wall thickness loss exceeding 90% of the standard wall thickness. Pitting corrosion is identified by a minimum wall thickness loss of 0.51 mm along the pipe string body. Annular corrosion is characterized by a radial span exceeding 50% of the pipe string circumference and an axial length less than twice the inner diameter of the pipe string. Linear corrosion is described as corrosion with a radial extent surpassing 30% of the string circumference and an axial length greater than double the inner diameter of the string.

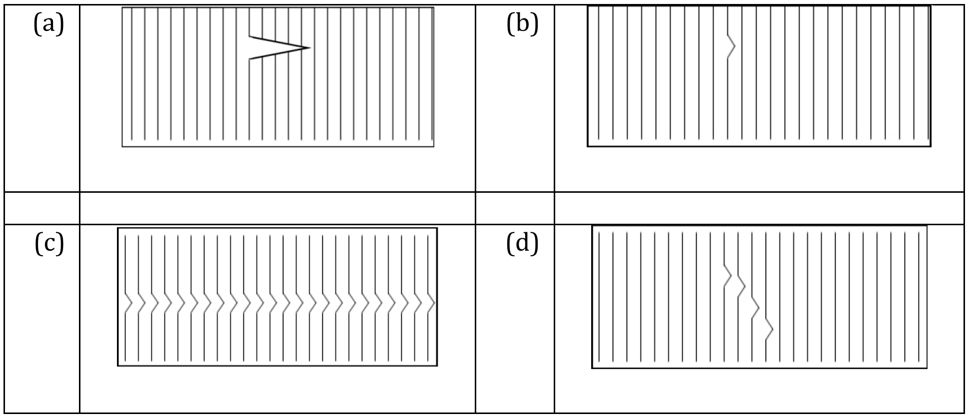

Figure 1. Types of Casing Corrosion. (a) Perforation;(b) Pitting corrosion;(c) Annular corrosion;(d) Linear corrosion.

3. Model Introduction

3.1. EllipticEnvelope

The EE algorithm leverages spatial clustering characteristics, assuming that normal data exhibits elliptical clustering. It involves fitting a boundary using robust covariance estimation and identifying points located significantly far from the boundary as outliers. The key procedure entails computing the covariance matrix and mean to define the ellipse, and determining outliers based on the Mahalanobis distance threshold between data points and the mean. The elliptical decision boundary is established through the eigendecomposition of the covariance matrix, with the Mahalanobis distance quantifying the deviation of data points from the centroid. The formulation of the elliptical equations is as follows:

$$\frac{(x-\bar{x})^2}{\lambda_1}+\frac{(y-\bar{y})^2}{\lambda_2}+\frac{(z-\bar{z})^2}{\lambda_3}=k^2 \tag{1}$$

Let λ represent the eigenvalues of the covariance matrix, where k denotes the coverage threshold determined by the contamination parameter.

The anomaly judgement criterion states that if the Mahalanobis distance D2 squared of point Pi surpasses the threshold k2, it is classified as anomalous.

$$D^2=(X-\mu)^2\Sigma^{-1}(X-\mu) \tag{2}$$

Here, D^2 represents the Mahalanobis distance squared, with X denoting the observed value, μ indicating the data mean, Σ representing the data's covariance matrix, and Σ^{-1} denoting the inverse of the covariance matrix.

3.2. Parameter Optimization with Robustness

A dynamic optimization approach utilizing statistical inference is proposed to address the issue of parameter sensitivity in a cascaded outlier detection model.

Initially, in the preliminary screening phase, the optimal contamination parameter for the elliptical envelope model is determined as contamination=0.05 (with a confidence level of 1-α=0.95) through fitting historical wellbore data distribution and employing 5-fold cross-validation. The fundamental principle is to minimize the error in normal data coverage. The EE algorithm, known for its robustness against interference, is grounded on Minimum Covariance Determinant (MCD) estimation. This method identifies a subset of samples with the minimum covariance determinant through iterative computation, accurately capturing the underlying data structure to mitigate the impact of outliers on parameter estimation. Furthermore, the algorithm effectively detects and mitigates the influence of anomalous data, thereby addressing the issue of false detection due to scaling distortions in practical industrial settings.

4. Results and discussion

4.1. Experimental Parameter Settings

As shown in Table 1, the key parameter (contamination) for the EllipticEnvelope model was determined through fitting historical data distribution and optimized via 5-fold cross-validation. Parameter tuning was conducted using grid search with a step size of 0.01 and a maximum of 100 iterations.

Table 1. Parameter Settings of the Cascade Method.

Parameter	Setting Value	Optimization Basis
contamination	0.05	Fitted to historical data distribution to determine the optimal contamination parameter for the Elliptic Envelope model
Downsampling Step	3	Computational time reduced by 47% with spatial resolution loss < 5%

4.2. Method Comparison

Using 2M data points from Well XX in the Ordos Basin, this study evaluates the efficacy of the EllipticEnvelope (EE)-based outlier detection method by comparing it with other unsupervised techniques, including Isolation Forest, DBSCAN, and a conventional industry-standard threshold method. The objective is to validate the performance of the EE algorithm in detecting casing corrosion. Isolation Forest identifies outliers by constructing random binary trees, DBSCAN detects outliers through density-based clustering, and the traditional threshold method assesses corrosion status according to API 5CT guidelines.

The evaluation metrics for corrosion detection include the following: accuracy, which indicates the proportion of correctly detected corrosion points among all detections, reflecting the model's overall classification capability; recall, which measures the proportion of actual corrosion points correctly identified, assessing the model's ability to capture corrosion characteristics and prevent missed detections; false alarm rate, representing the proportion of normal points incorrectly classified as corrosion, evaluating the model's capacity to suppress noise and interference; and Mean Absolute Error (MAE), which quantifies the average absolute difference between predicted and true values of wall thickness loss, suitable for assessing regression accuracy.

Table 2. presents a comparative analysis of the results from the four tested methods.

Method	Accuracy(%)	Recall(%)	False - Positive Rate(%)	MAE(mm)
Isolation Forest	82.1	75.3	8.7	1.8
DBSCAN	78.5	68.9	12.4	2.3
Threshold Method	70.2	62.1	15.6	3.1
Our Method	92.3	89.6	4.5	0.9

Figure 2 illustrates the comparative performance of various algorithms in detecting casing corrosion. The model demonstrates a notable improvement in detecting casing corrosion compared to conventional unsupervised outlier detection and threshold-based methods.

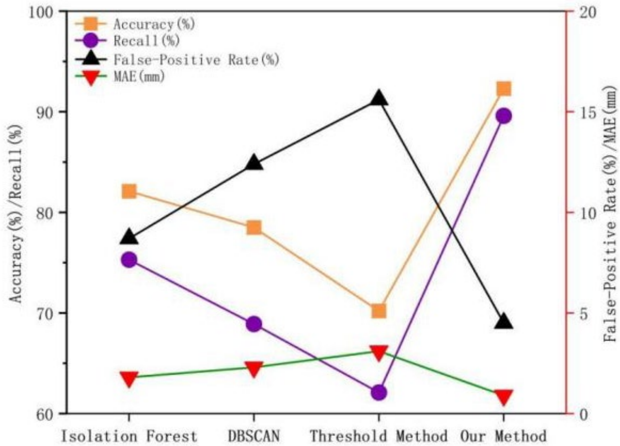

Figure 2. Comparison of Trends in Detection Results

4.3. Visualization Analysis

Figure 3 presents the interactive interface developed to visualize the spatial distribution of corrosion points, with each outlier mapped to its precise coordinates.

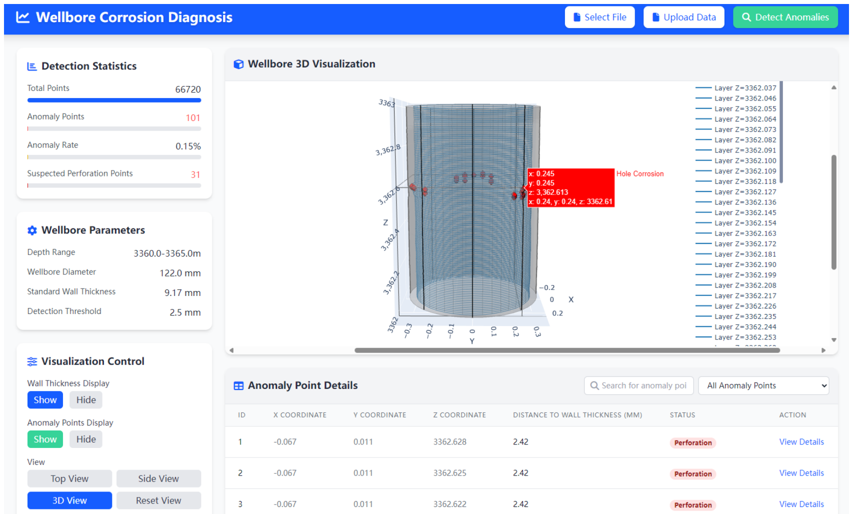

Figure 3. Cascaded Outlier Detection Interface

5. Couclusion

This paper presents an intelligent casing corrosion diagnosis method based on the EllipticEnvelope (EE) algorithm. By leveraging robust covariance estimation, the method constructs a spatial elliptical boundary for multidimensional logging parameters, enabling effective identification of abnormal patterns associated with various common corrosion types. Validation and comparative experiments were conducted using measured data from wells in the Ordos Basin. The results demonstrate that the EE-based approach achieves a casing corrosion detection accuracy of 92.3%, outperforming existing methods such as Isolation Forest. This improvement enhances the accuracy and reliability of downhole structural monitoring, providing a robust technical framework for casing inspection and downhole condition assessment.

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