Extraction Methods for Pipeline Weld Defect Features

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Abstract. This paper introduced weld defect features based on a digital X-ray image using texture and geometric feature parameters. An improved complete local ternary pattern (CLTP) algorithm was proposed according to these parameters to extract the texture features from the image, while the geometric feature values were obtained using the contour tracking method. Furthermore, the practicability of this method was demonstrated with an example.

1. Introduction
X-ray inspection has become a typical detection method used for industrial non-destructive testing, the results of which are vital for weld defect analysis and quality assessment. Radiography is currently used as a conventional discrimination method, using film for manual evaluation. However, manual film evaluation presents various challenges, such as a high subjective judgment error rate, low detection efficiency, and a workload that is too complex. In addition, it is difficult to complete all the work in a short time, while manual film evaluation is also affected by personal experiences to a large extent. To resolve the challenges presented by weld film evaluation, this paper proposes digital weld film management. This technology transforms the manual evaluation procedure into intelligent automatic computer processing. The extraction and calculation of the weld defect features allow the recognition of digital image defects on the weld seam. Furthermore, different weld defect standards allow various types of weld defects to be classified, significantly reducing human errors. Therefore, intelligent film evaluation technology exhibits considerable research potential in the field of non-destructive testing.

Liao and Jacobsen researched radiographic hardware equipment for detecting weld defects and proposed using scanners for digitally converting images for the first time [1]. Aokikdengren et al. improved the scanner and described how it could be combined with a camera to digitize the radiographs [2]. As early as 1968, Shlral of The University of Tokyo in Japan proposed the development and utilization of a computer software system for automatically detecting welding rays, taking the lead in research involving edge feature extraction and prediction boundary point extraction methods for radiographic films [3]. Lin examined image binarization, improved the method for extracting target parameters, and proposed a technique that directly used gray image change to extract the target parameters [4]. Shao et al. proposed the double threshold segmentation algorithm to eliminate the background area using the balanced welding method to analyze the waveform. This technique successfully resolved challenges, such as poor detection timeliness and low image signal-to-noise ratios in thick wall workpieces via algorithm fusion [5]. Professor Gao of Xi’an Shiyou University first used...
Ostu and Sobel operators to extract the effective area of weld defects, proposing the concept of gray density in the weld image [6].

2. Introduction of weld defect features
The feature selection process is mainly concerned with the geometric and texture feature extraction of weld defects. The macro and micro weld defects can be fused and extracted via threshold segmentation by organically combining the two. Furthermore, it is necessary to track and mark the position and shape of the weld defects to facilitate the subsequent edge detection.

2.1. Texture feature parameters of weld defects
The texture feature parameters of the weld defects are mainly calculated using the following four parameters, while all gray level co-occurrence matrices are represented by \( G(i, j) \) [7-9]:

1) Energy feature (ASM): It reflects the degree of uneven gray distribution in the image and the thickness of the internal texture of the weld defect. It represents the square sum of all gray level co-occurrence matrix elements in the weld defect image. When the values in the co-occurrence matrix are uneven or if the elements are concentrated, the ASM is more significant, becoming smaller if they are all equal. The ASM value reflects the uniformity of the image. The calculation formula is as follows:

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

(1)

2) Contrast (CON): It denotes the depth of the internal texture groove in the weld image, expressing its visual clarity. The deeper the texture groove, the greater the CON, and vice versa. The CON and gray level differences are more significant in the gray level co-occurrence matrix when a higher number of gray level elements are further away from the diagonal. The calculation formula is as follows:

\[
CON = \sum_{n=0}^{k-1} n^2 \left\{ \sum_{j=0}^{k-1} G(i, j) \right\}
\]  

(2)

3) Correlation (COR): It reflects the correlation of the local gray level in the image while measuring the similarity between the spatial gray level co-occurrence matrixes in different rows and columns of the weld image. The correlation is most significant when the values in the matrix elements are equal. When the difference is substantial, the correlation is more negligible. With a texture in the horizontal direction, the COR value of the matrix in the horizontal direction exceeds that of other directions. The calculation formula is as follows:

\[
IDM = \sum_{i=1}^{k} \sum_{j=1}^{k} \frac{G(i, j)}{1 + (i - j)^2}
\]  

(3)

4) Entropy (ENT): Since the texture feature information is an expression of image data, it not only represents the complexity of the weld image texture or the non-uniform degree of its internal information but also denotes a random measure of all the data of the weld image itself. If all the elements of the co-occurrence matrix display the largest randomness and are distributed in a decentralized way, and all the values of the spatial matrix are equal, then the entropy is larger. The calculation formula is as follows:

\[
ENT = -\sum_{i=0}^{k} \sum_{j=0}^{k} G(i, j) \log G(i, j)
\]  

(4)

2.2. Characteristic geometric parameters of weld defects
The geometric eigenvalues of the weld defects are extracted and calculated to obtain the sample parameters. This provides the geometric features of the weld defect area, establishing the model and parameters of its internal inscribed deformation and external circumscribed deformation. A schematic diagram of the external circumscribed rectangle of the defect is shown in Figure 1.
Figure 1. A schematic diagram of the external circumscribed rectangle of the object

According to the distribution and shape of common defects on the weld film, the feature values, such as roundness and the gray difference between the defects and the background, are often selected as the appearance feature values for defect identification. Furthermore, formula transformation is used to extract additional required geometric feature quantities [10, 11]. During the experiment, the following seven types of shape features were considered the basis for weld defect identification. The specific content and formula are as follows:

1. **Circularity** \( e \) was defined as: The first thing to determine is the area and perimeter. The formula of roundness is shown in (5).

\[
e = \frac{4\pi S}{C^2}
\]  

Where \( e \) is the circularity, \( S \) is the region area, and \( C \) is the region perimeter.

2. The gray difference between the defect and the background was denoted by \( \Delta h \): The average gray value of the base metal area on the weld image was \( Z_1 \), and the average gray value of the defect area on the weld bead was \( Z_2 \). The calculation formula of the difference is shown in (6).

\[
\Delta h = Z_1 - Z_2
\]

Calculation and analysis showed that when \( h \) was negative, it was preliminarily judged as a slag inclusion. When it was positive, the defect in this area was preliminarily judged as a pore.

3. The grayscale deviation of weld defect was recorded as \( \delta \): It was used to distinguish the round slag inclusion and round pore. The deviation of the slag inclusion was slight. The calculation formula is shown in (7).

\[
\delta = \frac{\sum Z_{\text{MAX}} - Z}{n}
\]

Where the maximum gray value of defect area is \( Z_{\text{MAX}} \), and the gray value of any point is \( Z \).

4. The equivalent area of weld defects was recorded as \( S / C \): This referred to the ratio of the region area of weld defects to the perimeter of the feature area, which was represented by \( S / C \). A smaller value caused the defects to display a slender, zigzag pattern and slender, which were often used to distinguish the crack.
(5) The ratio of the long axis to the short axis: This referred to the ratio of the long axis length to the short axis length in the target area. The calculation formula is as follows:

\[ G[2] = \frac{\sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2}}{\sqrt{(x_2 - x_3)^2 + (y_2 - y_3)^2}} = \frac{L_x}{L_y} \]  

(8)

Where \((x_1, y_1), (x_2, y_2), (x_3, y_3)\) are the coordinates of the outer circumscribed rectangle of the target area. The calculation formulas of the long axis and short axis are as follows:

\[ L_x, \text{ long axis: } L_x = \sqrt{(x_1 - x_3)^2 + (y_1 - y_3)^2} \]  

(9)

\[ L_y, \text{ short axis: } L_y = \sqrt{(x_2 - x_3)^2 + (y_2 - y_3)^2} \]  

(10)

(6) The ratio of the area to the perimeter: This represented a parameter used to describe the shape of the weld defects and played a specific role in distinguishing various types of defects. The ratio was smallest when the defects were close to a circle while increasing when the defects were further away.

(7) The position of the center coordinate relative to the center of the weld: This represented a relative parameter that described the position of the weld center in the film image. It was used to distinguish and identify incomplete penetration and fusion. The center position mark is shown in Figure 2, while its calculation formula is shown in (11).

\[ G[1] = \frac{d}{B_w} \]  

(11)

Where the \( G \) coordinate is relative to the center of the weld, \( d \) indicates the difference in distance between the center position of the weld defect and the centerline of the weld bead, and \( B_w \) indicates the weld width.

Figure 2. A schematic diagram of the center of gravity

3. Methods used for weld defect feature extraction

Weld defect extraction technology is essential for weld defect image recognition. Since the evaluation of weld defects is based on the entire film, both the local details and overall layout must be considered, necessitating examining the overall weld characteristics. Weld defect assessment usually occurs by observing the overall weld morphology, after which the distinction is based on the detailed division of the local weld film information. Therefore, a complete local ternary pattern (CLTP) model is proposed that can combine the local image information with the overall feature morphology to obtain better classification results.

3.1. Pipeline weld texture feature extraction technology based on the CLTP model

The main research content of this section introduces texture feature extraction, during which specific methods are used. The commonly used algorithms include the local binary pattern (LBP) and Gabor
wavelet. Therefore, this paper proposed an improved CLTP based on LBP to maintain the rich texture features.

(1) The introduction of LBP

The texture feature LBP was proposed by Ojala et al. [12]. The basic principle of binary encoding process of binary mode is to perform binary encoding on the grayscale difference between a pixel in the image and the pixels in the surrounding area, and finally apply the same to the binary process of the pixels in the entire image. The local binary mode can be defined by formula (12) [13-15]:

\[
LBP_{P,R}(x_c, y_c) = \sum_{p=0}^{P-1} s(g_p - g_c)2^p
\]

\[
s(x) = \begin{cases} 
1, & x \geq 0 \\
0, & x < 0 
\end{cases}
\]

Where \( P \) represents the number of pixels in the image, \( R \) denotes the neighborhood radius of the pixel, \( g_p \) signifies the gray value of the neighborhood pixels around a certain point, and \( g_c \) represents the gray value of the central pixel.

It is assumed that the local texture structure consists of specific neighborhood pixels represented by \( T \), including the geometric features of the image pixels with the gray level \( P+1 \) \((P > 0)\). Any of these values can be considered the starting position to proceed sorting in a clockwise direction, in which case the texture structure \( T \) can be represented by the following formula (13):

\[
T = t(g_0, g_1, \ldots, g_{P-1})
\]

Where \( g_0 \) is the center pixel of the local image, and \( g_1, \ldots, g_{P-1} \) is the \( P \) gray neighborhood pixel value of the center pixel.

The threshold \( TH \) is calculated via entropy \( ENT = -\sum_{i=1}^{P} \sum_{j=1}^{N} G(i, j) \log G(i, j) \):

\[
TH = \frac{\sum_{j=1}^{N} \sum_{i=1}^{P} (g_j - g_i) \cdot \zeta(g_j - g_i)}{P \times N}
\]

\[
\zeta(g_j - g_i) = \begin{cases} 
1, & g_j - g_i > 0 \\
0, & g_j - g_i \leq 0 
\end{cases}
\]

Where \( g_i \) represents the pixel of the center point, \( g_j \) denotes the pixel of its neighborhood, \( P \) signifies the number of neighborhood pixels, and \( N \) represents the number of multiple pixels in the calculation area. The weight \( 3^p \) is distributed to each \( s(g_p - g_c) \), and the formula can be used to obtain the unique LTP code, which is represented by \( LTP_{P,R} \).

\[
LTP_{P,R} = \sum_{p=0}^{P-1} s(x)3^p
\]

Where \( R \) denotes the neighborhood radius.

The actual algorithm was applied to the example according to the LBP, as shown in Figure 3.
In the example of LBP algorithm, Figure 3 (a) represents a 3*3 sample, denoting the pixel and its surrounding 8-point neighborhood. Figure 3 (b) shows the parameter values for sample introduction and selection. Figure 3 (c) indicates the mode difference calculations for the samples. Figure 3 (d) shows the value after LBP processing. Therefore, the final LBP value of this sample can be determined according to the calculation presented in Figure 3 (d) and the corresponding weight table. The mode is 20020100.

(2) CLTP

The extraction of weld texture features involves boundary definition and local information refinement. Although the traditional method uses the LBP to describe the texture features, the accuracy of texture description is easily affected. Therefore, the algorithm used during processing requires continuous improvement. A CLTP mode [16,17] is proposed, including three core operator center descriptors, symbol descriptors, and size descriptors, which are expressed as \( \text{CLTP}_C \), \( \text{CLTP}_S \), and \( \text{CLTP}_M \), respectively. The modified \( \text{CLTP}_C^* \), \( \text{CLTP}_S^* \), and \( \text{CLTP}_M^* \) are obtained after transforming the operators. The calculation process is as follows:

\[
\text{CLTP}_S^* = \sum_{p=0}^{p-1} s_1(x)3^p \\
\begin{aligned}
s_1(x) &= \begin{cases} 
2, & x \geq TH \\
1, & 0 \leq x < TH \\
0, & x < 0
\end{cases}
\end{aligned}
\]

\[
\text{CLTP}_M^* = \sum_{p=0}^{p-1} s_2(x)3^p
\]
\[ s_2(|x|) = \begin{cases} 
2, & x \geq b \times TH \\
1, & a \times TH \leq x < b \times TH \\
0, & x < a \times TH 
\end{cases} \quad (19) \]

\[ CLTP^*_C = \begin{cases} 
1, & x \geq TH_1 \\
0, & x < TH_1 
\end{cases} \quad (20) \]

Where \( P \) represents the number of pixels, \( TH \) denotes the threshold value, \( a, b \) represents the custom constant and \( TH_1 \) signifies the average value of the image pixels.

When the difference between the center pixel and the neighboring pixel is marked as \( d_p \), the calculation formula in (21) is applied.

\[ d_p = g_p - g_c \quad (21) \]

Where \( g_p \) represents the gray value of neighboring pixels and \( g_c \) denotes the gray value of the center pixel.

Then, the \( LTP_{P,R}^{8x2} \) mode is used to transform the coding values, and \( CLTP^*_S, CLTP^*_M, \) and \( CLTP^*_C \) are shown in Figure 4.

![Figure 4](image-url)

**Figure 4.** The CLTP mode calculation chart

Figure 4 (a) shows a 3*3 sample block with a center pixel of 38, while the eight pixels in the neighborhood are [27, 72, 69, 32, 25, 43, 26, 88]. In Figure (b), \( \bigodot \) represents the gray value of the central pixel and \( TH = 24 \) is the calculated threshold. The local difference is calculated, and the operator results are [-11, 34, 31, 50, 26, 43, 25]. In Figure (c), the ternary coding vector of the local difference sign \( CLTP^*_S \) is [1, 2, 2, 0, 10, 1, 2]. In Figure (d), the operator values of \( CLTP^*_M \) are [1, 2, 2, 0, 10, 1, 2]. In Figure (e), \( TH_1 = 47.75 \), and the average value is calculated via [27, 72, 69, 32, 25, 43, 26, 88], while the \( CLTP^*_C \) value of CLTP is [0, 0, 0, 0, 0, 0, 0, 1].

(3) Case analysis
The weld film of the steel pipeline was 350 mm in length and 80 mm in width, displaying pore defect features. The film image was intercepted, and the width was changed to 50 mm. The CLTP method was used to recognize the texture of the weld film, while different feature parameter values were selected for extraction. The recognition situation is shown in Figure 4.

Figure 5. The stomatal texture feature extraction
It could be concluded from Figure 5(1-6) that the description values of the weld texture features provided different descriptions due to various parameters. In Figure 5, \(a=0.4\) and \(B=0.6\) display obvious advantages, with the \(CLTP\_M\) value being the most distinct feature.

3.2. Geometric feature extraction from pipeline welds using the contour tracking method

The detection area of the weld defects must be marked first to obtain multiple geometric parameters. This paper used the contour tracking method to mark the weld defect detection area [18-20]. First, the marking was explained, which involved a description of the external geometry and boundary, as well as the relationship between the regions. The defect marking is shown in Figure 6.

![Figure 6](image-url)  
Figure 6. A schematic diagram of the rectangular boundary of the weld defect area

(1) The introduction of the contour tracking method principle

The chain code technology is used according to the shape of the defect to extract the geometric feature value and save the information regarding the weld defect area. The area marked by the chain code determined the number and the corresponding position of the weld defects in the weld image. The chain code usually occurred in a 4-channel and 8-channel direction, as shown in Figure 7.

Each line segment was coded in one direction from the starting point and along the boundary using 4-chain and 8-chain coding methods. The coding of an object ended when the starting and end points met.

![Figure 7](image-url)  
Figure 7. A diagram of the 4-connected and 8-connected chain codes
The 4-connected chain code uses the basic pixel point to mark the weld defects. First, a basic pixel point was pointed in four adjacent directions, after which 1-4 was selected in an anticlockwise direction. The same was true for the 8-connected chain codes. To determine a pixel point, it was pointed in the direction of the eight adjacent contacts surrounding it, after which 1-8 was selected in an anticlockwise direction. A coordinate axis was determined according to the assumed image, while the coordinate origin deviation represented the coordinate discrepancy in the specified pixel transformation, as shown in Table 1.

Table 1. The chain code tracking coordinate system

| Chain code value | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|-----------------|---|---|---|---|---|---|---|---|
| X-coordinate deviation value | 1 | 1 | 0 | -1 | -1 | -1 | 0 | 1 |
| Y-coordinate deviation value | 0 | -1 | -1 | -1 | 0 | 1 | 1 | 1 |

Figure 8 depicts a schematic diagram of the contour tracking algorithm, in which the location of the white point represents the internal area of the weld defect, while the black points denote the boundary points of the weld edge detection. The schematic diagram of the defect tracking is shown in Figure 8. The weld image was processed and saved in the form of a matrix on a computer.

The contour tracking process of the defect image occurred as follows: The pixels were scanned in the X-axis direction on the coordinate axis of each weld image, while the initial point was set as that closest to the bottom of the image. As shown in Figure 8, the preset boundary point was black, the inner part of the weld defect was white, and a 45° anticlockwise direction was used for marking. When the pixel in the next direction was black, it was marked and saved as the boundary point. Otherwise, it was searched for according to a predetermined direction until encountering the black point, representing the new boundary starting point. The search process for the black boundary point was repeated. The final condition of the algorithm required identifying the last black pixel of the defect point in the image and then returning to the first detection point until all the boundary points were found and saved. This also represented the process of searching and saving the defect mark of the entire weld image.

(2) Case application of chain code tracking

The chain code tracking algorithm of the geometric weld defect features could mark multiple faults in the weld defect area. It could also calculate and save the relevant information, significantly aiding the recognition and classification of weld defect features while preserving and processing the existing weld defect image information. MATLAB was used for the image tracking and marking process. The strip slag defect image is shown in Figure 9, while the image after defect marking is shown in Figure 10.
The texture and geometric features were selected as the processing objects to determine the locations and eigenvalues of the weld defects. The length-width ratio, circularity, equivalent area of geometric features, contrast, entropy, energy, and texture feature correlation were extracted. Furthermore, to increase the practicability and efficiency of the CLTP algorithm during the feature extraction from the weld image, the six parameters in Chapter 3 were selected after calculating the criteria. The feature parameter data was obtained, as shown in Table 2.

| Length-width ratio | Gray difference | Contrast degree | Entropy | Circularity | Equivalent area |
|--------------------|-----------------|-----------------|---------|-------------|-----------------|
| 4.21               | 1434.65         | 0.52            | 6.61    | 0.24        | 1.14            |
| 7.00               | 1609.30         | 0.48            | 7.57    | 0.12        | 1.22            |
| 16.00              | 1254.34         | 1.33            | 2.01    | 0.36        | 1.32            |
| 8.00               | 543.22          | 1.98            | 3.22    | 0.12        | 1.83            |
| 1.13               | 2361.13         | 0.32            | 4.34    | 0.88        | 0.81            |
| 1.98               | 866.22          | 0.63            | 3.28    | 0.79        | 1.78            |
| 1.18               | 863.12          | 0.65            | 2.35    | 0.87        | 1.89            |
| 2.12               | 1243.33         | 0.32            | 4.43    | 0.91        | 1.12            |
| 4.56               | 332.34          | 0.87            | 3.39    | 0.22        | 2.15            |
| 22.32              | 241.54          | 0.78            | 2.38    | 0.13        | 3.12            |
| 12.00              | 1324.31         | 0.42            | 4.33    | 0.34        | 1.12            |
| 8.00               | 1123.22         | 0.39            | 3.36    | 0.46        | 1.18            |

After calculating the geometric features and texture eigenvalue algorithms of the selected samples and establishing the standard, six were selected to distinguish the types and categories of the weld defects.
4. Conclusion
First, the types of weld defects and their various image features are introduced in detail, while the basis for defect classification is provided. A CLTP algorithm is proposed based on the LTP classification algorithm to extract the texture features of the weld defects according to the geometric, texture, and morphological characteristics. The CLTP method is superior to the simple shape feature and traditional LBP texture feature description methods regarding classification accuracy. It can also extract the geometric features of the weld with the aid of contour tracking method.

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