An Efficient Method Using Mathematical Morphology for Crack Detection in Pipeline Images

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Abstract

Defects on the Pipeline surface such as cracks cause main problems for governments, specifically when the pipeline is covered under the ground. Manual examination for surface defects in the pipeline has several disadvantages, including varying standards, and high cost. An algorithm based on mathematical morphology and curvature evaluation for the detection of cracks is proposed. We define a crack as a bright pattern and locally linear. Mathematical Morphology is very well modified to this explanation. After experimentation, edge detection method proposed in this paper is efficient.

1. Introduction

Pipelines are often one of the major infrastructures of every country. Nearly all countries use thousands of miles of pipe that bring purified water to homes, petroleum and gas to refinery and carry away wastewater. Many governments spend considerable cost to maintenance and rehabilitation (M&R) of pipelines. Hence, assessing the condition of pipelines is one of the important issues in countries' economy.

Among the pipeline defects such as holes, cracks, fissures, and so on, cracks are more important because they are one of the earliest indications of degradation of the pipeline structures and detecting them at an early stage can help prevent sudden failures. Therefore, crack detection on pipeline surface is the major object now but it is not solved completely so far [1] especially when the contrast between the crack and the background is low.

Several techniques have been proposed for crack detection.[2] and [3] used the Wavelet transform to detect cracks on concrete surfaces. [4] used a Canny filter and the Wavelet transform for the crack detection.also, The wavelet transform has been successfully applied to crack localization in beam structures [5]-[7]. The advantage of the wavelet transform is its multi-resolution property, which allows the efficient identification of local features of a signal [8]. [9] suggested a robust and high-efficiency model for segmentation and the calculation of distress statistics of massive pavement images which is based on multi-scale space. [10] proposed a method for detection of crack falls within the scope of the Bayesian framework. In [11] an algorithm for the extraction of both transversal and horizontal cracks from pavement images was presented. [12] introduced an efficient method for crack detection employing percolation-based image processing. [13] considered the direction of cracks as a feature, and then they applied it to detect cracks on granite slabs and drains.

In this paper, we present an algorithm based on mathematical morphology to detect cracks, and also this algorithm is efficient for images in which the contrast between crack and background is low. Finally, we compare this algorithm to other crack detector methods and we present a conclusion.

2. Basic mathematical morphological operations

Mathematical morphology is a new mathematical theory which can be used to process and analyze the images. In this section we remind some basic definitions of morphological operators. More information can be found in [14]–[21].

We define a two-dimensional (2D) images whose intensity range is [Imin,Imax]as a functional F: R2→ [Imin,Imax], and a 2-D structuring element as a functional B: R2→B where B is the set of the neighborhoods of the origin. We will only consider structuring elements invariant by translation, that are identified with a subset of R2, and we refer to linear structuring when this subset is a line segment. We define basic operators, with respect to the structuring element B with scaling factor e, image F, and point P0 ∈ R2:

Erosion: $\varepsilon_B^e(F)(P_0) = MIN_{P\varepsilon P_0+e.B(P_0)}(F(P))$; (1)

Dilation: $\delta_B^e(F)(P_0) = MAX_{P\varepsilon P_0+e.B(P_0)}(F(P))$; (2)

Opening: $\gamma_B^e(F) = \delta_B^e(\varepsilon_B^e(F))$; (3)

Closing: $\phi_B^e(F) = \varepsilon_B^e(\delta_B^e(F))$; (4)

Top hat: $TH_B^e(F) = F - \gamma_B^e(F)$; (5)

The basic mathematical morphological operators are dilation and erosion and the other morphological operations are the combinations of the two basic operations. Although the theory of mathematical morphology often present on binary images, it has the natural extensions to gray-scale images. Generally, dilation causes objects to grow or thicken and increases the grey-scale value of the image, while erosion causes objects to shrink or thin and decreases the grey-scale value of the image. The specific manner and extent of the thickening or shrinking are controlled by structuring element. The opening operation is somewhat like erosion in that it smoothes the contour of an object, breaks narrow isthmuses, and eliminates thin protrusions. Closing is somehow similar to dilation and it also tends to smooth sections of contours but, as opposed to opening, it generally fuses narrow breaks and long thin gulfs, eliminates small holes, and fills gaps in the contour.

3. The proposed morphological crack detection algorithm

We can identify the linear bright shapes using mathematical morphology. An opening and eroding with a linear structuring element will remove a crack or part of it when the structuring element cannot be fitted in the geometry of the crack. In the other word, when they have orthogonal directions, the structuring element is longer than the crack width. If an image is opened along a class of linear structuring elements, a maximum of top-hats along each direction will brighten the cracks. The structuring elements for maximum of top-hats must be large enough to remove big cracks; therefore, the maximum of top-hats will recovery a lot of noise. Hence, we remove noise using a geodesic reconstruction of the eroded images into the original image F0 before tacking the maximum of top-hats. The geodesic reconstruction preserves most of the cracks and it is defined as:

$$F_{op} := \gamma_{F_0}^{rec}(\underset{i=1\ldots18}{Max}\{\varepsilon_{B_i}(F_0)\}) \tag{6}$$

Each structuring element (every 10°) is 12-pixels long (1-pixel wide). The size of structuring element is based on the range of crack widths that are of importance to us (fig 1). In the reconstructed image Fop, every bright zone whose diameter is less than 12 pixels will be removed. The maximum of top-hats on the filtered image Fop will enhance all cracks.

We assume that any nonzero point in the picture has a Dominant direction, and thus can be considered as part of some crack pattern. We refer to the curvature whenever it is the curvature in the cross direction, which is defined for every pixel in the image. Its evaluation using the Laplacian operator on a top-hats operated image has been

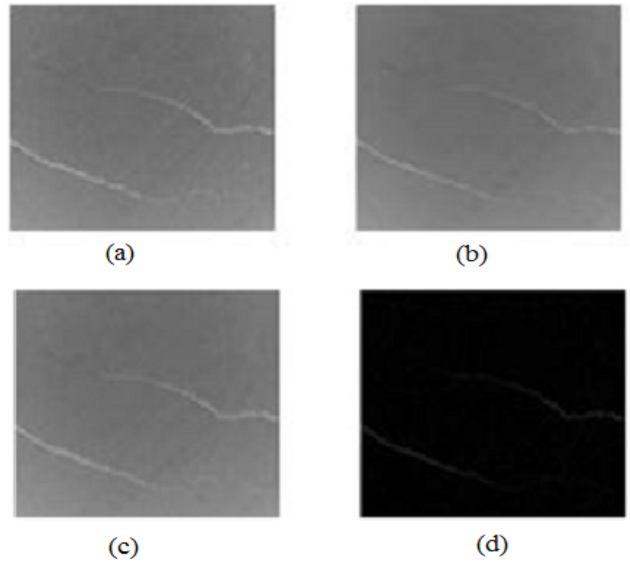

Figure 1. (a)Original image, (b) maximum of eroding, (c) geodesic reconstruction, and (d) maximum of top- hats.

analytically discussed and presented by Zana and Klein [22]. The Laplacian of Fop obtains a good estimation of the curvature (fig 2). Then a linear opening by reconstruction of size 23 removes enhanced noises [23]. The following is our summarized algorithm:

$$F_{op} := \gamma_{F_0}^{rec}(\underset{i=1\ldots18}{Max}\{\varepsilon_{B_i}(F_0)\}) \tag{7}$$

$$F_{\max-th} := \underset{i=1\ldots18}{Max}\{F_{op} - \gamma_{B_i}(F_0)\} \tag{8}$$

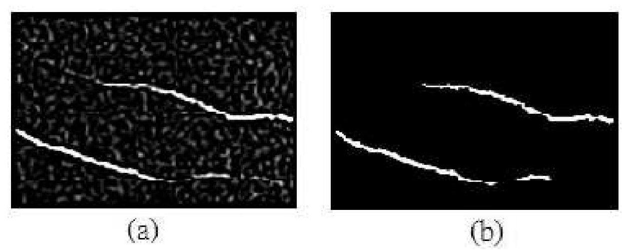

Figure 2. Laplacian images highlighted around zero (positive values in white and negative values in black): (a) before and (b) after final step and threshoding.

The maximum of top-hats reduces small bright noise and improves the contrast of all linear parts. Cracks could be segmented with a manual threshold on Fmax-th, but most images would be noisy thus requiring further treatment by curvature evaluation

$$F_{lap} := Laplacian(Gaussian_{\sigma=2}^{width=12_{px}}(F_{\max-th})) \tag{9}$$

Laplacian filters are derivative filters used to detect areas of rapid change (edges) in images. Usually images are smoothed (e.g., using a Gaussian filter) before applying the Laplacian because derivative filters are very sensitive to noise. This two-step process is called the Laplacian of Gaussian (LoG) operation. Then we perform a linear opening by reconstruction of size 29 to remove the enhanced noises.

$$F_{final} := \gamma_{F_{lap}}^{rec}(\underset{i=1...18}{Max}\{\gamma_{B_i}^{2}(F_{lap})\}) \quad (10)$$

At the end, cracks are light objects on a dark background. One way to extract the cracks from the background is to select a threshold T that separates them. Therefore, for automatically extracting, we use Otsu's thresholding method [24]. The abstract of this threshold algorithm is as follows. Supposed the pixels of the image have V intensity levels {0, 1, 2,…, V-1}. The number of pixels that have intensity level v is n_v and the total number of pixels is N = n0+n1+n2+…+nv-1. To simplify, the histogram is normalized as a discrete probability density function:

$$P_v = \frac{n_v}{N} \quad P_v \geq 0 \quad (11)$$

Suppose the pixels are divided into two classes C0 and C1 (background and crack) by a threshold k; C0 denotes pixels with levels [0, 1,…,k-1] and C1 denotes pixels with levels [k+1,…, V-1]. Otsu's method chooses the threshold value k which maximizes the between-class variance:

$$\sigma_B^2 = \omega_0(\mu_0 - \mu_T)^2 + \omega_1(\mu_1 - \mu_T)^2 \quad (12)$$

Where

$$\omega_0 = \sum_{v=0}^{k} p_v \quad \text{and} \quad \omega_1 = \sum_{v=k+1}^{v-1} p_v \quad \text{and} \quad w_T = \sum_{v=0}^{v-1} vp_v$$

$$\mu_0 = \frac{\sum_{v=0}^{k} vp_v}{w_0} \quad \text{and} \quad \mu_1 = \frac{\sum_{v=k+1}^{v-1} vp_v}{w_1}$$

4. Evaluation of Crack Detectors

The evaluation of the crack detectors is performed by comparing automatically detected cracks with manually detected cracks (reference cracks) extracted by an expert. In this paper, a simple matching method called 'buffer method' [25] is used for performance evaluation of our algorithm. In this method, a buffer of constant width is constructed around the cracks in two steps. In the first step, we construct a buffer of constant width around the reference crack data by using a morphological dilation operation with structuring element of size 5×5. The parts of the extracted data in the buffer are considered as matched and are denoted as true positive, and let TP be the number of true positive pixels. The unmatched extracted data is denoted as false positive and let FP be the number of false positive pixels. In the second step, we construct the same buffer around the extracted crack data, and the parts of the reference data within the buffer are considered as matched. The unmatched reference data is denoted as false negative, and let FN be the number of false negative pixels. Let TC be the number of true crack pixels (manually extracted crack pixels) and N be the number of all pixels of the image. Now, the probability of detection P_d and probability of false-alarm P_{fa} can be defined as below:

$$P_d = \frac{\text{Number of detected crack pixels}}{\text{Number of true crack pixels}} = \frac{TP}{TC} \quad (13)$$

$$P_{fa} = \frac{\text{Number of false-alarm pixels}}{\text{Number of non-crack pixels}} = \frac{FP + FN}{N - TC} \quad (14)$$

5. Experimental results

Our Proposed algorithm was tested on 170 images taken from petroleum pipelines of Iran and compared with a variety of existing methods for crack detection. Also, we have evaluated the performance of our algorithm on the images modified by salt and pepper noise. Finally, we compared proposed algorithm with Sinha's algorithm [23] applied to images acquired from various cities in North America. All our images were captured in digital using a Canon SX100 IS camera. The image size was $500 \times 375 \times 3$ [pixels].The operating environments of experiments are configured as follows: OS: Windows Vista, Language: Matlab 7.6, CPU: Intel(R) Core (TM2) 2.5 GHz. Two main advantages of our algorithm in comparison to Sinha's algorithm are that our algorithm is faster than Sinha's algorithm, and our algorithm detects the cracks of the images in which the contrast between the cracks and the background is low better than Sinha's algorithm. Table I shows the experimental results. Figure 3 and 4 give the resulting images.

6. CONCLUSION

In this paper, we proposed an efficient mathematical morphology algorithm to detect pipeline image cracks. The experimental results show that the algorithm is more efficient for pipeline image denoising and crack detecting than the previous crack detection algorithms like Canny edge detector, Prewitt edge detector, Laplacian of Gaussian operator, morphological gradient operation, and Sinha's algorithm.

Table 1. Comparison between results of different method

Method	Average Probability of detection (Pd) without noise	Average probability of false-alarm (P_{fa}) without noise	Average Probability of detection (Pd) with noise	Average probability of false-alarm (P_{fa}) with noise	Average Time [s]
Canny edge detector	%39.78	%4.006	%40.06	%6.06	0.716
Prewitt edge detector	%40.92	%0.95	%41.51	%2.32	0.62
Log edge detector	%40.52	%1.01	%40.87	%2.61	0.58
morphological gradient operation	%60.61	%1.76	%40.49	%3.62	0.091
Sinha's algorithm	%85.2	%0.75	%82.4	%0.74	18.1
proposed algorithm	%90.7	%0.58	%91.33	%0.59	13.4

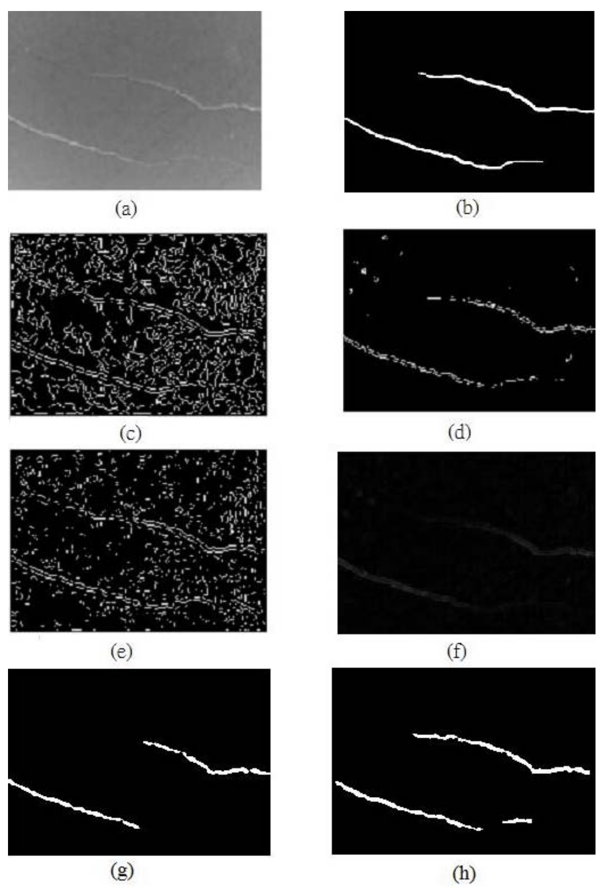

Figure 3. Edge detection algorithms on crack pattern image:(a) original image,(b) Manually extracted image,(c) Canny edge detector, (d) Prewitt edge detector, (e) Log edge detector, (f) morphological gradient operation,(g) Sinha's algorithm (h) proposed approach.

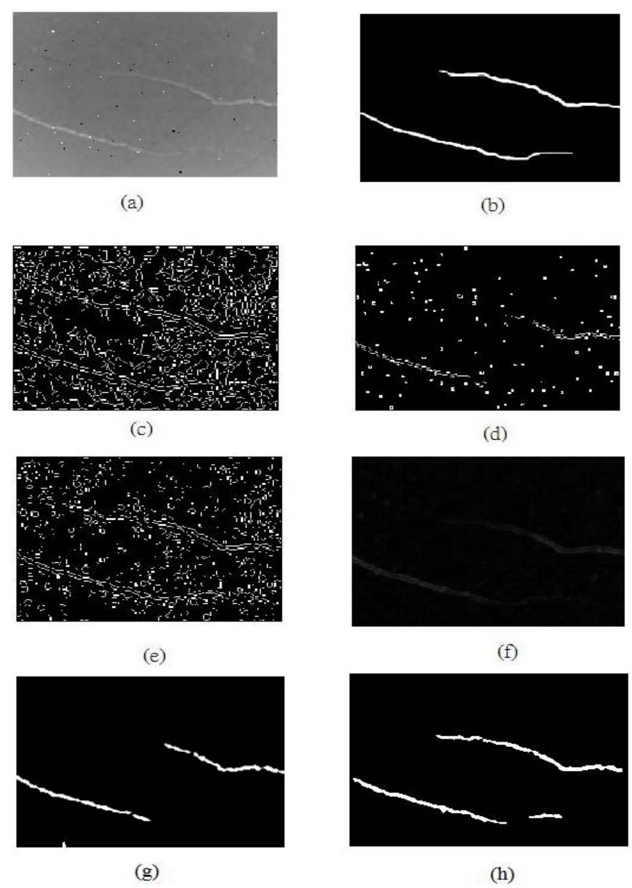

Figure 4. Edge detection algorithms on crack pattern image with noise salt and pepper: (a) original image,(b) Manually extracted image,(c) Canny edge detector, (d) Prewitt edge detector, (e) Log edge detector, (f) morphological gradient operation,(g) Sinha's algorithm(h) proposedapproach.

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