Localization of Fissure in Water Pipe in an Urban Network to Minimize Leakage

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Abstract

In this paper, we propose an effective method for detection and localization of fissure. The proposed scheme uses a set of features; it is based on the characteristics
of texture and geometric aspects. First, we detect regions of texture that can contain fissure, later; we decompose the multi-segment texture regions using the standard expectations maximizing (EM) segmentation resulting binary images with "k" containing components with different levels of gray. Finally, we analyze the components in a suitable mask, which results from the previous step to distinguish fissure from non-fissure component.

The experimental results of the method are evaluated by a test on a database composed of 200 images.

**Keywords:** Image processing, fissure, pipe, robot, algorithm, pixels.

1. **Introduction**

The availability of drinking water is a major factor contributing to the growth of the world. However, a significant amount of water distribution transport from processing plants to the point of consumption is never completely delivered to its destination. The cause of the leak depends on several factors; the most important is the presence of cracks in water pipes. These pipes should be inspected before use and those that are defective must be placed out of service. We propose in this paper a method based on image processing to sort the healthy behaviors of cracked pipes. For this we will use an adjustable navigating robot different inside diameter of the pipe with two embedded camera for image acquisition in different positions, a transmission system and distance information of the image processing system. Once this method was not available provided the important price components used now with technological developments, the availability of equipment and the price approaching this method is promising.

2. **Image Processing and its contribution mechanical**

The image processing is increasingly used as a tool of control and management. Thus, it helps to increase the flexibility and productivity of production workshops, help with maintenance, to better understand the quality of products (compliance with ISO 9000, for example, industry standards) to solve problems previously unanswered.

The contribution of image processing and mechanical metallurgy is very broad include eg metrology (2D and 3D) and structural analysis for the study of materials and control of industrial quality control as it allows the geometry of mechanical parts and detect very small defects imperceptible to our eyes and / or mechanical devices
Organization of crack detection system

(Fig.1: Design with CATIA robot image acquisition software)

The acquisition mechanism is a robot to navigate within a pipe with two cameras, and a lighting system. This mechanism is adaptable to different pipe diameters; it is fixed in advance to adhere well to the pipe wall. This robot is controlled remotely, sailing along the pipe lines. Two on-board cameras take pictures at different positions of the surface of the pipe and through the transmission system images generated in the treatment are transmitted in real time of the system. These images are processed and filtered according to pictures with images without cracks and fissures in a program that uses algorithms development that we will present in the
3 Texture analyses

The texture analysis step uses the observation that the crack in the images has distinct properties distinguishing background crack. So we can deduce that the crack is present in the areas of image texture. In this case, the objective of this first step of the algorithm is to extract the regions of texture filtering and smooth. The texture analysis model divides an image into grayscale in two types of regions: smooth texture. We decompose an image of N macro block size. The size of the cracks varies between 5x5 pixels and 30x90 pixels.

The number N of blocks varies and depends on the size of the image. For each MB the average edge intensity is considered. We adopt the gradient magnitude to obtain the edge image.

Let MB(X, Y) denote the MB at location (X, Y) in an image.

The edge intensity of the MB (X, Y) is calculated by:

$$MBI(X,Y) = \sum_{(i,j) \in MBI(X,Y)} V(i,j)$$  \(1\)

Where V (i, j) represents the amplitude of the gradient intensity I (i, j) at the location (i, j), using masks of extended finite convolution to estimate the partial derivative with:

$$V(i,j) = \sqrt{\left(\frac{dI(i,j)}{dy}\right)^2 + \left(\frac{dI(i,j)}{dy}\right)^2}$$  \(2\)

A MB must be over the edge intensity of the TV threshold to be classified as texture MB. Otherwise, it belongs to the smooth regions. TV is determined by:

$$TV = \beta \sum_{(i,j) \in MBI(X,Y)} \frac{MBI(X,Y)}{N}$$  \(3\)

Where β is the weighting factor, its value has been experimentally set to 0.75. [1] [2]

4 Segmentation algorithms

The goal of the segmentation process is to decompose the image obtained in the previous step in multi-segment representing regions with similar levels of gray. In our approach, an algorithm for maximizing the standard expectations (EM) is used for the components segment texture regions. We classify the pixels into classes of K, so that we get K segmented images.

The EM algorithm is an iterative algorithm for computing the probability or a maximum a posteriori estimation. Each iteration of the algorithm is a waiting step, followed by a step of maximizing. Segmentation is applied to the histogram of the
Localization of fissure in water pipe

gray image assuming that the image is a combination of random fields. We model the image intensities as a function of the combination of simple random process $K$:

Every single process is taken to represent the image regions with similar levels of gray. We believe that belonging to a given class follows a normal distribution:

$$f(x / \theta_k) = \frac{p_k}{\sqrt{2\pi\sigma_k}} e^{-\frac{(x-\mu_k)^2}{2\sigma_k^2}} \quad (4)$$

With : $k$ : the class number and $\theta_k = (\mu_k, \sigma_k)$ : a mixture of distribution $x$ : the pixels vector ; $k$ : the class number and $\theta_k = (\mu_k, \sigma_k)$ : a mixture of distribution $x$ : the pixels vector ; $k$ : the class number and $\theta_k = (\mu_k, \sigma_k)$ : a mixture of distribution

Where :

$\mu_k$ : vector of class means and $\sigma_k$ : vector of class variances

And :

$P_k$ : vecteur of a priori probability $k$

$$P_k = \frac{1}{K} \quad \text{where} \ k \ \text{is number of classes}$$

The $k$ individual processes are combined into probabilistic mixture model according to:

$$f(x) = \sum_{k=1}^{K} \pi_k f(x / \theta_k) \quad (5)$$

The EM algorithm is an iterative algorithm decomposed on 3 steps:

The first one is the initialization of a priori probabilities, means, and variances of each class. That we calculate:

$$L = \sum_{k=1}^{K} \log f(X) = \sum_{i=1}^{n} \log \sum_{k=1}^{K} f(x_i / \theta_k) = \prod_{i=1}^{n} \sum_{k=1}^{K} f(x_i / \theta_k) \quad (6)$$

With $x_i$ in the pixel belongs to the class $k$.

The final step is the maximization; we calculate the parameters by maximizing the expected likelihood found on the no waiting. These parameter estimates are then used to determine the distribution of pixels in the next step of waiting. After classification of the pixels into $K$ classes, each class label for a binary image (mask) is generated.

5 The experimental results

The basis for the tested contains healthy images and fractured images. The size of the cracks varies between 5x5 pixels and 30x90 pixels. We must eliminate the bottom 25 pixels detections. The contours of the fissure are identified by a morphological
gradient operator category using expansion contours are grouped according to the

criterion of proximity to form regions. Generally, the detection algorithms images are evaluated using techniques developed

for information systems research. Specifically, two measures: precision (P) and recall (R) are commonly used because they intuitively convey the quality of results.

\[
\text{Recall} = \frac{\text{No. of correctly retrieved items}}{\text{No. of relevant items in database}}
\]

\[
\text{Precision} = \frac{\text{No. of correctly retrieved items}}{\text{Total no. of retrieved items}}
\]

To choose the size of the morphological operator, we plotted the precision / recall curves in Figure 1. These curves are set in relation to the size of the operator which is a compromise between the detection of the smallest fissure and eliminating noises that could be confused with fissure.

(Fig. 2: Recall/Precision curves)

We note that the size of 25 pixels is the best compromise that provides a high accuracy while designing a tau acceptable recall. It is this value that was used in the testing phase illustrated in the following paragraph. The figures 3 and 4 show the treatment performed on images with or without defects. The intermediate steps are presented. The following images (Figure 3 (b) and Figure 4 (b)) are obtained after threes holding. When images do not show any defects, the dark regions are randomly distributed in the image. These regions appear in the image noise. In the presence of cracks, dark regions form rows of larger size. We apply a closure to connect pieces of neighboring cracks. Similarly, we apply an
opening to eliminate noise: regions insignificant size. The figures (Figure 3 (c) and Figure 4 (c)) show the images obtained after this step.

![Fig.3 : Image with fissure](image1)

![Fig.4: Image with no fissure](image2)

6 **Comparison of the results of tests:** We conducted tests on an image database consisting of 100 images and 100 healthy images with cracks. The program we have developed has for goal for separating
images fissured from the images without fissures. The following table 1 shows a comparison of our results with other authors working on the same subject.

<table>
<thead>
<tr>
<th>Method</th>
<th>Precision rate (%)</th>
<th>Recall rate (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ashida [7], [5]</td>
<td>55</td>
<td>46</td>
</tr>
<tr>
<td>H W David [7]</td>
<td>44</td>
<td>46</td>
</tr>
<tr>
<td>Wolf [7]</td>
<td>67</td>
<td>46</td>
</tr>
<tr>
<td>Liu [6], [3]</td>
<td>66</td>
<td>46</td>
</tr>
<tr>
<td>Proposed method</td>
<td>70</td>
<td>59</td>
</tr>
</tbody>
</table>

Table 1: Comparison and performance

7 Conclusion
In this paper, a new system that detects and locates the fissure in water pipes before use in the drinking water network. Detection and localization are based on images taken in a wide variety of conditions such as lighting, pose and background. The algorithm has been proposed on the basis of image decomposition pixel background regions in an image and the use of geometrical rules to identify fissure. Several points were as detailed analysis of the background and fissure. The experimental results showed that our method is effective in locating fissure in water pipes. The algorithm can be used to control the structure mechanical components in civil engineering.

References


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