Automated Analysis and Detection of Cracks in Underground Scanned Pipes

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Abstract

Closed Circuit Television (CCTV) surveys are used widely in North America to assess the structural integrity of underground pipes. The video images are examined visually and classified into grades according to degrees of damage. The human eye is extremely effective at recognition and classification, but it is not suitable for assessing pipe defects in thousand of miles of pipeline images due to fatigue, subjectivity, and cost. This paper presents ongoing research into the automatic assessment of the structural condition of underground pipes for the purpose of preventive maintenance by municipalities.

1. Introduction

The National Science Foundation (NSF) has estimated the total U.S. investment in civil infrastructure systems at $US 20 *trillion.* The investments in underground pipeline distribution systems represent a major component of this figure. Many of these systems are eroding due to aging, excessive demand, misuse, and neglect, as shown in Figure 1. Many of the methods used to assess and interpret the condition of underground pipe systems have been inadequate because they were based on inspection only after failure. At present, the assessed condition of underground pipes is based on the subjective visual inspection of CCTV surveys [1], resulting in handicapped financial justifications of rehabilitation work. An automatic pipe inspection system is required, based on CCTV surveys, which can extract and assess conditions to ensure accuracy, efficiency, and economy of pipe examination. This paper presents an analysis of the detection of defects in underground sewer pipes.

CCTV surveys are conducted using remotely controlled vehicles carrying a television camera through an underground pipe. The data acquired from this process consist of videotape, photographs of specific defects, and a record produced by the technician. Diagnosis of defects depends on experience, capability, and concentration of

Figure 1. Underground pipe image showing a large hole, scanned by PSET (Core Corp.) in the city of Albuquerque.

the operator, making the detection of defect error prone. Although underground imaging technology has made substantial strides in recent years, the basic means of analysis are unchanged: a technician is required to identify defects on a monitor. The research of this paper seeks to address this latter limitation.

Most of the literature concerning the detection of defects in civil structures deals with the analysis of pavement and concrete/steel distresses [2], analyses which are not directly applicable to underground pipe inspection. The approach proposed in this paper is based on local detection of linear structures. The scanned images are obtained by Pipe Scanner and Evaluation Technology (PSET) camera, developed by Core Corp., California and TOA Grout, Japan [3]. Typical scanned images with various defects are shown in Figures 2 (a) & (b).

2. Image Feature Extraction

In the computer vision literature one can find various techniques addressing different types of data, including natural and artificial textures, synthetic aperture radar images, and magnetic resonance images. In analysing underground pipe scanned image data, one needs to

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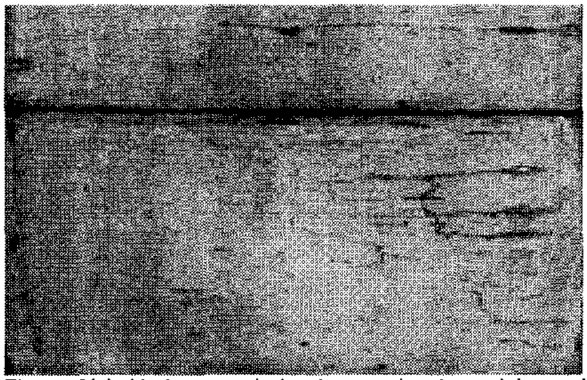

Figure 2(a). Underground pipe image showing a joint and few minor cracks.

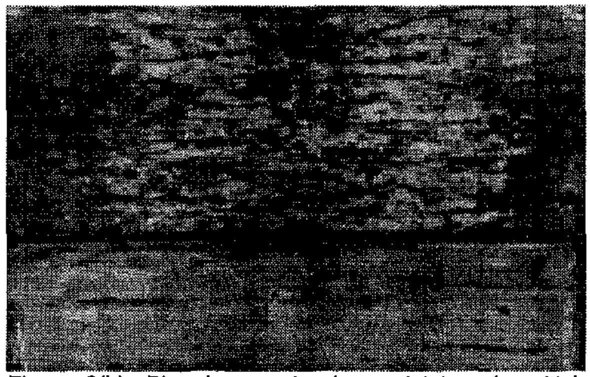

Figure 2(b). Pipe image showing a joint and multiple cracks, most severely above the joint.

consider complications due to the inherent noise in the scanning process, irregularly shaped cracks, as well as the wide range of pipe background patterns. One of the major problems is detecting defects (especially cracks) that are camouflaged in the background of corroded areas, debris, patches of repair work, and areas of poorly illuminated conditions.

In the past 20 years, many approaches have been developed to deal with the detection of linear features on optic [4] or radar images [5]. Most of them combine two criteria: a local criterion evaluating the radiometry on some small neighborhood surrounding a target pixel to discriminate lines from background and a global criterion introducing some large-scale knowledge about the structures to be detected.

Concerning the local criterion, most of the techniques used for pavement distress detection in scanned images are based either on conventional edge or line detectors [6,7]. These methods evaluate differences of averages, implying noisy results and variable false-alarm rates [8]. In addition, local criteria are in many cases insufficient for edge or line detection, and global constraints must be introduced [9]. For instance, dynamic programming is used to minimize some global cost functions, as in the original algorithm of Fishler [10] and its improvement [4]. Hough-transform-based approaches have also been tested for the detection of parametric curves, such as straight lines or circles [11]. Tracking methods are another possibility. They find the minimum cost path in a graph by using some heuristics, for instance, an entropy criterion [12]. Energy minimization curves, such as snakes, have been applied [13]. The Bayesian framework, which is well adapted for taking some contextual knowledge into account, has been widely used [14].

The approach proposed in this paper falls within the scope of the Bayesian framework. Since our aim is to detect the defects present in an image, contextual knowledge on the scale of pixels is insufficient and results in numerous, small, disconnected segments. However, on the scale of segments, *a priori* knowledge allows for the detection of cracks. Thus, detection of crack is performed in two steps. In the first step, crack-segment candidates are detected. In the second step, cracks are obtained by cleaning and linking operations.

3. Detection of Cracks

The algorithm begins with performing a local detection of cracks. This is based on the fusion of the results from two crack detectors D1 and D2, both taking the statistical properties of image into account. Crack detector D1 is based on a ratio edge detector for which an in-depth statistical study of its behavior is given in Lopes et. al. [15]. Detector D2, which has emerged from this research, uses the normalized centered correlation between two populations of pixels. Both responses from D1 and D2 are merged to obtain a unique response as well as an associated direction in each pixel. The detection results are post-processed to provide candidate segments. Figure 3 shows the different steps of the proposed crack detection algorithms.

3.1. Ratio Crack Detector D1

The ratio crack detector was introduced in [8] and statistically studied in [15]. This crack detector D1 is derived from the coupling of two edge detectors on both sides of a region. Let index 1 denotes the central region and indexes 2 and 3 both lateral regions, as shown in Figure 4. The amplitude of pixel x is noted A_x, so that the empirical mean μ_i of a given region i having n_i pixels is: $\mu_i = \left(\frac{1}{n_i}\right)\sum_{x\in i} A_x$. The response of the edge detector between region i and j is defined as r_{ij}.

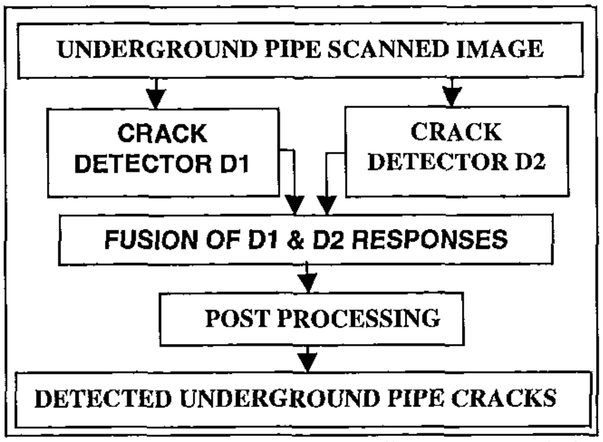

Figure 3. Diagram showing the different steps of the proposed crack detection algorithm.

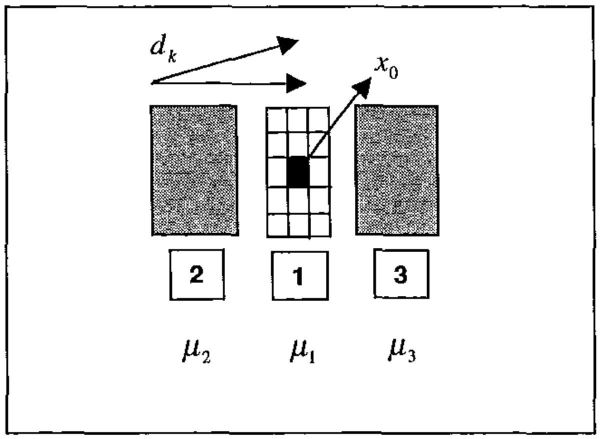

Figure 4. Crack model used by the two crack detectors.

$$r_{ij} = 1 - \min\left(\mu_i \big/ \mu_j , \mu_j \big/ \mu_i \right)$$

and the response to D1 as $r = \min(r_{12}, r_{13})$, the minimum response of a ratio crack detector on both sides of the crack structure. With detector D1, a pixel is considered as belonging to a crack when its response r is large enough, i.e., higher than some *a priori* chosen threshold $r_{\min}$.

The geometric shape of the filter (Figure 4) is adequate, but many directions have to be tested. Besides, the width of a crack not being precisely defined, several widths for region 1, 2, and 3 are tried. Thus, considering N_d directions d_k, $k \in \{1, \ldots, \mathrm{N}_d\}$ for the crack detector. Because of the chosen length of the mask, at least eight directions have to be used to guarantee that any crack, whatever its direction, has the same detection probability.

3.2. Cross-Correlation Crack Detector D2

This approach is inspired from the work of Yakimovsky [16]. The ideal crack best approximating the amplitude in a given window Wx_0 around a pixel x_0 and for a given direction $d_k\left(k \in \{1, \ldots, \mathrm{N}_d\}\right)$ is computed by using the Yakimovsky's operators. The operators of Yakimovsky assume that edges are interfaces between sets of points, each set being described by a normal distribution. The mathematics for distribution parameter comparison is used to form a function of crack strength in an area.

$$s = \left[\frac{\left(\sigma_0^2\right)^{m+n}}{\left(\sigma_1^2\right)^m \left(\sigma_2^2\right)^n} \right]$$

where,

σ_0^2 = Variance for region 1, 2, and 3 taken together.

$$= \frac{\left[m\sigma_1^2 + n\sigma_2^2 + m(\mu_0 - \mu_1)^2 + n(\mu_0 - \mu_1)^2 \right]}{(m+n)}$$

μ_0 = Mean for region 1, 2, and 3 taken together.

$$= (m\mu_1 + n\mu_2) \big/ (m+n)$$

m, μ_1, σ_1^2 = Samples, mean, variance for region 1.

n, μ_2, σ_2^2 = Samples, mean, variance for region 2 and 3.

A pixel is considered as belonging to a crack when its response s is large enough, i.e., higher than some *a priori* chosen threshold $s_{\min}$. Once this ideal crack is defined, the validity of the hypothesis "there is a crack in x_0 with the direction d_k" is tested by using the normalized centered cross-correlation between pixels of Wx_0 and the ideal crack.

The crack detector D2 is defined by the minimum response ρ (cross-correlation coefficients) of the filter on both sides of the structure $\rho = \min(\rho_{12}, \rho_{23})$. A crack is detected when the response is higher than the decision threshold $\rho_{\min}$.

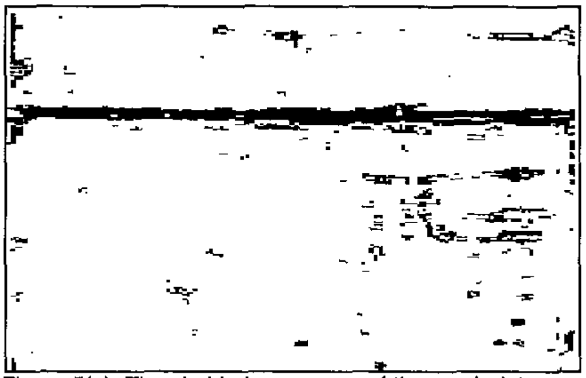

Figure 5(a). Thresholded responses of the crack detectors for minor cracks in the underground pipe.

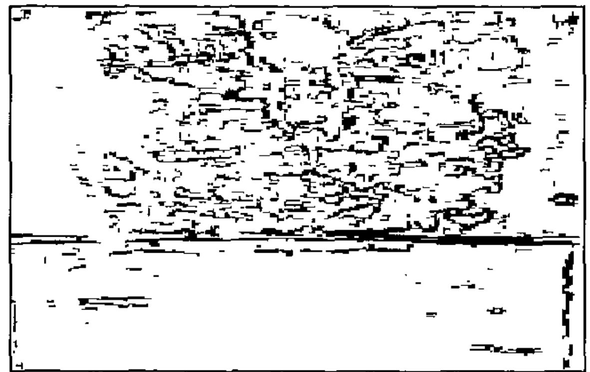

Figure 5(b). Thresholded responses of the crack detectors for multiple cracks in the underground pipe.

4. Fusing Responses from D1 and D2

The responses from both the detectors are merged using an associative symmetrical sum $\sigma(x, y)$, as defined in [17].

$$\sigma(x, y) = \frac{xy}{1 - x - y + 2xy}, \text{ obtained for } f(x, y) = xy$$

Symmetrical sums represent 'hybrid' aggregation operators. More generally, any associative symmetrical sum has the following behavior:

- Conjunctive if
  $$\max(x, y) < \tfrac{1}{2} : \sigma(x, y) \leq \min(x, y),$$
- Disjunctive if
  $$\min(x, y) > \tfrac{1}{2} : \sigma(x, y) \geq \max(x, y),$$
- Compromise if
  $$x \leq \tfrac{1}{2} \leq y : x \leq \sigma(x, y) \leq y,$$

and the reverse inequality holds if $y \leq \tfrac{1}{2} \leq x$. This illustrates the variable behavior of σ, depending on the values to be combined. Thus such operators are context independent variable behavior operators (CIVB) [17].

5. From Pixels to Segments

Starting from the response of the crack detector at each pixel, segment primitives are generated by the following procedures, whose aim is to suppress local false alarms and obtain a 'cleaner' binary result by using simple heuristic rules.

- Since isolated pixels have little chance of belonging to a crack, a pixel suppression step is first performed. For each pixel kept with direction $d_k \left(k \in \{1, \ldots, N_d\}\right)$, other selected pixels are searched with a direction close to d_k in an angular beam around it. If none is found, the pixel is suppressed.
- In order to suppress other dubious responses due to small local structures, the best line in a given neighborhood is detected. To do so, a local Hough transform [18] is applied on a 5x5 pixel tiling of the image. Each pixel is attributed a vote for its associated direction. Only the pixels greater than pre-assigned threshold values are kept, the others are suppressed.
- The next step aims to fill small gaps between selected pixels. Pixels are linked in the direction d_k of any pixel; the pixels belonging to an angular beam around d_k with a direction close to d_k and at a distance less than four pixels are linked to it.
- Since cracks are obtained as segment chains, they are not precisely located. For crack visualization, a simplified snake based method has been used [19].

6. Results on Scanned Pipe Images

In this paper, an almost unsupervised method has been proposed for detecting the cracks, as seen in underground pipe scanned images. The method includes both high and low level treatments. All the parameters for the detection of cracks are determined experimentally. Thresholded responses of the crack detectors after fusing and linking operations are shown in Figure 5(a) and 5(b).

The first image [Fig. 2(a)] is a part of Toronto sewer pipeline system, showing some minor cracks in the pipe surface. In this case, the crack detection step performs quite well [Fig. 5(a)] detecting most of the crack structures in the image. The second scanned image [Fig. 2(b)] is from the city of Boston. This image has dark background pipe surface with multiple cracks, most severely above the pipe joint. In this case, the crack detection step performed well, but results are noisy with many false alarms. The cleaning and linking operations shown to be a powerful method, which is able to fill gaps between the detected segments providing a map of the crack pipe surface, while suppressing most of the false-alarm detection [Fig. 5(b)]. In fact, the results are close to those that could be obtained by a trained human operator.

7. Conclusion

This paper address the problem of underground pipe crack detection using an approach based on Bayesian framework. The local crack detector deal with scanned images considering their statistical properties. Since there does not appear to exist a single coherent model suitable for reliable detection of pipe cracks, it is essential that some means of integrating information from multiple image operators and knowledge source be devised. This research has provided a simple mechanism for integrating the information provided by the two operators for the specific task of crack detection. Plans for future work include the continuing development of fully automated technique for defect detection in the underground pipe scanned images.

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