An Automated Intelligent Fault Detection System for Inspection of Sewer Pipes

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Keywords: intelligent system, automation, fault detection, sewer pipe system.

Pipe walls in sewer systems are prone to be damaged due to aging, traffic and chemical reactions, through which inflow such as rainwater and groundwater seeps into pipe systems. Regional city government reports state that this inflow amounts to approximately 30% of the total flow. In addition to the inflow of groundwater into sewer pipes, outflow from damaged systems also occurs, contaminating the surrounding environment.

Basically, maintenance or inspection process starts by collecting information about the utility. It highlights useful information about conditions of the utility such as the number and the location of faults.

Conventional inspection of a sewer pipe system is carried out using a cable-tethered robot with an onboard video camera system. An operator remotely controls the movement of the robot and the video system. By this video-supported visual inspection, any notable damages or abnormalities are recorded in video stream. The reliability of this system depends on the experience of an operator. The system is also prone to human error, and tends to be time consuming and expensive. Consequently, effective automated online techniques to identify and extract objects of interest such as cracks are of immediate concern.

All previous works focused on specific types of faults in pipes and none of them proposes a method for detecting various types of faults. Accordingly, an automated fault detection system is not available in the real world. In this study, we propose a method for detecting faulty areas based on images, and propose an automated intelligent system designed to facilitate diagnosis of faulty areas in a sewer pipes system. The system utilizes image analysis and efficient techniques for providing the location and the number of faults in a sewer pipe system.

An overview of the automated intelligent fault detection system is shown in Fig.1. Digital images of sewer pipes taken by the camera system on the inspection robot are given to the fault detection system. The system, then, extracts a global ring ROI image to which edge enhancement is applied as preprocessing.

Next, a newly defined measure of horizontal similarity is computed in order to extract candidates for visible faulty area in the ring ROI areas. Conjecture here is that the measure of similarity between images without faulty area is large. Hence, we focus on the area where the horizontal similarity value is smaller than a horizontal threshold, \( t_h \), ranged between 0 and 1. Next, we extract a rectangular ROI and compute the vertical similarity value in the candidate faulty areas. Here, the area with vertical similarity value smaller than a vertical threshold, \( t_v \), is defined as a faulty area. The proposed approach can detect even faint faults in this rectangular ROI area. Finally the detected faults and its locations are compiled as a report. Here the location information on faults is provided by sensors on the robot such as an encoder, IR and a laser scanner.

We have proposed an intelligent system for detecting faulty areas automatically and implemented it in a real time system to solve the “real-world” problems in civil robots. In contrast to the conventional manual system, the proposed system can automatically detect faults and run in real time. Its detection performance is 100%, when the false positive rate is 34%. This ratio is acceptable for sewer inspection, and the reduction of time and cost are realized.
An Automated Intelligent Fault Detection System for Inspection of Sewer Pipes

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Automation is an important issue in industry, particularly in inspection of underground facilities. This paper describes an intelligent system for automatically detecting faulty areas in a sewer pipe system based on images. The proposed system can detect various types of faults and be implemented in a real time system. The present paper describes system architecture and focuses on two modules of image preprocessing and detection of faulty areas. The proposed approach demonstrates high performance in detection and reduction of time and cost.

Keywords: intelligent system, automation, fault detection, sewer pipe system.

1. Introduction

Pipe walls in sewer systems are prone to be damaged due to aging, traffic and chemical reactions, through which inflow such as rainwater and groundwater seeps into pipe systems. Regional city government reports (1) state that this inflow amounts to approximately 30% of the total flow. In addition to the inflow of groundwater into sewer pipes, outflow from damaged systems also occurs, contaminating the surrounding environment (2)-(4).

Basically, maintenance or inspection process starts by collecting information on the utility. It highlights useful information on conditions of the utility such as the number and the location of faults.

Conventional inspection of a sewer pipe system is carried out using a cable-tethered robot with an onboard video camera system. An operator remotely controls the movement of the robot and the video system (Fig.1). By this video-supported visual inspection, any notable damages or abnormalities are recorded in video stream. The reliability of this system depends on the experience of an operator. The system is also prone to human error, and tends to be time consuming and expensive. Consequently, effective automated online techniques to identify and extract objects of interest such as cracks are of immediate concern.

Most previous works (5) focused on specific types of faults in sewer pipes such as displaced joints and surface cracks. Carino (6) gives a detailed overview of crack detection strategies such as infrared thermography, stress wave propagation methods and a ground-penetrating radar. Many detection strategies are developed assuming specific pipe materials. Since widely used materials such as concrete and clay have heterogeneous compositions, it makes applications of simple fault detection methods problematic.

Widely used techniques for steel pipes such as the one by Stavroulakis et al. (7) are not applicable to PVC or concrete pipes due to their nonconducting characteristics. Given feature detection methods with appropriate sophistication and sensitivity, low cost and general-purpose systems such as video cameras can play an important role in fault detection of sewer pipes.

Robust detection of cracks and other faults in sewer pipes based on sensory data is an important challenge. Bernatzki et al. (8) introduced a method for detecting small cracks in oil and gas pipelines. Raw ultrasonic data were transformed into time-frequency representation by the wavelet transform. Edges were detected by...
the real part of wavelet coefficients. Artificial neural networks were also used for classification.

Yoshimura et al. (9) described applications of an inverse analysis method based on neural networks and a finite element method to the identification of cracks in solid objects using laser and ultrasonic sensors. They used Error Propagation Coefficients to evaluate the accuracy of a neuro-based method for crack identification. They are able to identify surface defect with a detection error rate of 2.4%–12.0%, and the depths with an accuracy of 0.6%–4.1%.

For high dimensional spatially distributed data, wavelets may provide useful feature detection. Mojsilovic et al. (10) used Haar wavelets for decomposition and classification of myocardial tissue images. Gunatilake et al. (11) introduced a mobile robot platform that provided images in real time for remote aircraft surface inspection. A widely practised crack detection algorithm is applied under directional lighting. It is a two-step multi-resolution edge detection method: a region of interest (ROI) is first converted into those with multiple resolutions by successive smoothing, followed by edge detection at each resolution. Wavelet-based filters are used for the conversion of ROI into those with multiple resolutions and for estimation of intensity variation for multi-resolution edge detection.

All above previous works focused on specific types of faults in pipes and none of them proposes a method for detecting various types of faults. Accordingly, an automated fault detection system is not available in the real world. In this study, we propose a method for detecting faulty areas based on images, and propose an automated intelligent system designed to facilitate diagnosis of faulty areas in a sewer pipes system. The system utilizes image analysis and efficient techniques for providing the location and the number of faults in a sewer pipe system.

The rest of the paper is organized as follows. The next section describes the proposed system and its components, and focuses primarily on two modules designed for image preprocessing and detection of faulty areas. Section 3 presents experimental results, and section 4 concludes the paper.

2. Proposed System

As we mentioned in introduction, in the conventional inspection systems, any notable damages or abnormalities in sewer pipe are detected by an operator. This system, therefore, is prone to human error, and tends to be time consuming and expensive. To overcome this difficulty, we propose an automated intelligent fault detection system. An overview of the proposed system is shown in Fig.2. Digital images of sewer pipes taken by the camera system on the inspection robot are given to the fault detection system. The system, then, extracts a ring ROI image, to which edge enhancement is applied as preprocessing.

Next, a newly defined measure of horizontal similarity is computed in order to extract candidates for visible faulty area in the ring ROI areas. Conjecture here is that the measure of similarity between images without faulty area is large. Hence, we focus on the area where the horizontal similarity value is smaller than a horizontal threshold, \( t_{h} \), ranged between 0 and 1. The horizontal threshold is a value between 0 to 1 and change of this value directly affects the number of detected faulty images in this step. Next, we extract a rectangular ROI and compute the vertical similarity value in the candidate faulty areas. Here, the area with vertical similarity value smaller than a vertical threshold, \( t_{v} \), is defined as a faulty area. The proposed approach can detect even faint faults in this rectangular ROI area. The fault detection module demonstrates high detection performance based on the similarity in ring ROI and rect-
define an average image of the panoramic image (Fig.4)

the panoramic image (width=942 pixel, height=500 pixel) is created from the extracted ring ROI image. We
with the width, \(w\), of panoramic image.

2.2 Detecting Faulty Areas In the last step, the panoramic image (width=942 pixel, height=500 pixel) is created from the extracted ring ROI image. We define an average image of the panoramic image (Fig.4) with the width, \(w_1 = 50\) pixel, and the height, \(h_1 = 50\) pixel. Then, we use a measure of similarity between the average image and panoramic image by Eq.(3).

Suppose we have a set of images without fault. A conjecture here is that the measure of similarity between images without faulty area is large. Hence, the area with small horizontal similarity than a horizontal threshold, \(t_{th} \), can be detected as a candidate faulty area.

\[
x = r \cos \theta, \quad y = r \sin \theta \quad \text{................. (1)}
\]

Because of the variation of brightness in a faulty area in sewer pipes, edge enhancement in the following steps is applied to the panoramic image.

(1) Convert the RGB into the brightness (Y).

\[ Y = 0.3 \times R + 0.6 \times G + 0.1 \times B \quad \text{................. (2)} \]

(2) Use a Gaussian filter to reduce noise.

(3) Detect edges. There are many methods for edge detection. Most of them are grouped into two categories: Gradient and Laplacian. In this paper, we use the Sobel and Prewitt Gradient operators, and the Laplacian operator.

\[
C(x) = \frac{1}{w_1 \times h_1 \times 255} \sum_{i=0}^{h_1} \sum_{j=0}^{w_1} (255 - |I(i + x, j) - \bar{I}(i, j)|)
\]

\[ x = (0, 25, ..., 875) \]

\[
\bar{I}(i, j) = \frac{1}{N_1} \sum_{k=0}^{N_1} I(i + k, j) \quad \text{.................. (3)}
\]

where \(I(i, j)\) is the brightness of the pixel at \((i, j)\), and \(x\) is the pixel coordinate in the horizontal axis in the panoramic image. \(\bar{I}\) is the average of brightness at \((i, j)\). Then, we focus on the candidate faulty area. We extract a rectangular ROI and compute the vertical similarity value (Fig.5) in this area to improve the detection rate based on the following equation.

\[
C(y) = \frac{1}{w_2 \times h_2 \times 255} \sum_{m=0}^{8} \sum_{i=0}^{w_2} \sum_{j=0}^{h_2} (255 - |I(i, y + j) - I(i, y + 5m)|)
\]

\[ y = (0, 5, ..., 40) \quad \text{.................. (5)} \]

where \(w_2 = 50\) pixel, \(h_2 = 10\) pixel. Finally, the area with vertical similarity value smaller than a vertical threshold, \(t_{thv}\), is detected as a faulty area. The proposed approach can detect even faint faulty areas in this rectangular area. Fig.5 illustrates the computation of autocorrelation value in the rectangular ROI area.

3. Experimental Results

3.1 A Guideline to the Faults Ranking in the Real World Japan Sewage Works Association (JSWA) \(^{(1)}\) classified three ranks (A,B and C) for various faults in sewer pipe system. Most visible faults defined as rank A, visible faults as rank B and hardly visible faults as rank C (see Fig.6). Also, JSWA defined the corresponding task to be done at each rank in Table 1.

Based on the above table, we can say, the automated system which is able to detect the faults in rank A and B is acceptable for sewer pipe inspection.

3.2 Evaluation of Proposed Method We evaluate the proposed method for detection of faulty areas using 253 images with 9 types of faults in Table 2 provided by a sewer inspection company. The image size is 640 x 480 pixel.
Fig. 6. An example of different ranks of cracks.

Table 1. Corresponding task to be done each rank.

<table>
<thead>
<tr>
<th>Levels</th>
<th>The inspection result</th>
<th>Corresponding task to be done</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>too much rank A faults</td>
<td>repair immediately</td>
</tr>
<tr>
<td>2</td>
<td>too much rank B faults +</td>
<td></td>
</tr>
<tr>
<td></td>
<td>a few rank A faults</td>
<td>by a simple maintenance,</td>
</tr>
<tr>
<td></td>
<td></td>
<td>repairing can extend by 5 years</td>
</tr>
<tr>
<td>3</td>
<td>too much rank C faults +</td>
<td></td>
</tr>
<tr>
<td></td>
<td>a few rank B faults +</td>
<td>by a simple maintenance,</td>
</tr>
<tr>
<td></td>
<td>no rank A faults</td>
<td>repairing can extend</td>
</tr>
<tr>
<td></td>
<td></td>
<td>more than 5 years</td>
</tr>
</tbody>
</table>

Table 2. The number of categorized images detected from sewer pipe images.

<table>
<thead>
<tr>
<th>Category</th>
<th>The number of images</th>
<th>A rank images</th>
<th>B rank images</th>
<th>C rank images</th>
</tr>
</thead>
<tbody>
<tr>
<td>crack</td>
<td>34</td>
<td>23</td>
<td>7</td>
<td>4</td>
</tr>
<tr>
<td>water infiltration</td>
<td>6</td>
<td>4</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>root invasion</td>
<td>25</td>
<td>17</td>
<td>6</td>
<td>2</td>
</tr>
<tr>
<td>pipe break</td>
<td>27</td>
<td>23</td>
<td>3</td>
<td>1</td>
</tr>
<tr>
<td>pipe gap</td>
<td>16</td>
<td>10</td>
<td>4</td>
<td>2</td>
</tr>
<tr>
<td>packing gap</td>
<td>8</td>
<td>5</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>mortar</td>
<td>11</td>
<td>9</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>an alien substance</td>
<td>11</td>
<td>7</td>
<td>3</td>
<td>1</td>
</tr>
<tr>
<td>landslide</td>
<td>7</td>
<td>4</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td>Non-Faulty Image</td>
<td>106</td>
<td>102</td>
<td>29</td>
<td>16</td>
</tr>
<tr>
<td>Total</td>
<td>253</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

We use 3 types of edge detection operators, Sobel, Prewitt, and Laplacian, for comparison of the ability of detection in ring ROI area. Here, “true positive” is defined as the ratio of the number of correctly detected faulty images to the total number of faulty images. Similarly, “false positive” is defined as the ratio of the number of non-faulty images classified as faulty to the total number of non-faulty images. Fig.7 illustrates false positive versus true positive for different edge detection operators when horizontal threshold is changed from 0.8 to 1 by an increment of 0.1. In ring ROI areas, the Sobel and Prewitt operators show almost the same performance, and is superior to the Laplacian operator.

We use F-test to clarify statistical significance of the difference between the variances of two different edge detection operators, Sobel and Prewitt. First we compute the binomial distribution for Sobel and Prewitt at all 21 horizontal threshold values. Two examples of the binomial distribution computing for $th_h = 0.8$ and $th_h = 0.9$ are shown in Fig.8. Next, the random samples are generated according to these probability distributions and displayed as histograms (see Fig.9).

Then, the F-test is calculated based on random samples. As is well known, the hypotheses for the F-test are:

- $H_0$: there is no difference between the two variances.
- $H_1$: the difference between two variances is significant.

If the F value is greater than the critical value for the specified level of significance, we reject the $H_0$. Table 3 shows results of the F-test for $th_h = 0.8$ and $th_h = 0.9$.

Since F-value is larger than the critical value, the null hypotheses $H_0$ is rejected. We choose the Sobel as a suitable edge detection operator.

Fig.10 illustrates examples of detection of faulty areas by the Sobel operator in ring ROI areas. Figs.10(b) and (d) show the successfully detected cases, marking the faulty areas with green circles. Failure sometimes occurs due to the false positive rate in ring ROI area. (Fig.10(f))

To achieve high detection rate, we choose a high horizontal threshold value in the horizontal similarity com-
An Automated I.F.D System for Inspection of Sewer Pipes

Horizontal threshold, \( th_h = 0.8 \)

Fig. 9. Generate random samples from probability distributions for \( th_h = 0.8 \) and \( th_h = 0.9 \).

Table 3. Output from the F-test for equality of variances for \( th_h = 0.8 \) and \( th_h = 0.9 \).

<table>
<thead>
<tr>
<th>( th_h )</th>
<th>Sobel Mean</th>
<th>Prewitt Mean</th>
<th>Variance</th>
<th>Number of samples</th>
<th>DF</th>
<th>( F )-value</th>
<th>Level of significance</th>
<th>( F ) critical value</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.8</td>
<td>4.762</td>
<td>4.762</td>
<td>54.391</td>
<td>21</td>
<td>20</td>
<td>0.598</td>
<td>0.05</td>
<td>0.471</td>
</tr>
<tr>
<td>0.9</td>
<td>4.762</td>
<td>4.762</td>
<td>41.391</td>
<td>21</td>
<td>20</td>
<td>0.904</td>
<td>0.05</td>
<td>0.471</td>
</tr>
</tbody>
</table>

Horizontal threshold, \( th_h = 0.9 \)

Next, we aim to find a suitable horizontal threshold in rectangular ROI areas using Sobel operator. Fig. 12 shows the performance of detection in rectangular ROI areas using Sobel operator for four different horizontal thresholds when vertical threshold is changed from 0.8 to 1 by an increment of 0.1.

As in the traditional statistical test, we aim at maximizing the true positive rate, keeping the false positive rate at a predetermined level called the level of significance. To observe the differences between different horizontal thresholds, the Cost is defined as the following:

\[
\text{Cost} = (1 - \text{true positive value}) \times 0.9 + (\text{false positive value} \times 0.1) \tag{6}
\]

The true positive value is weighted by 0.9 for keeping high affect in the cost. The cost for all horizontal thresholds is computed and results for four of them is shown in Fig.13. Horizontal threshold value of 0.97 shows the lowest cost.

Next, we focus on different ranks when horizontal thresholds is set to 0.97 and vertical threshold is changed from 0.8 to 1 by an increment of 0.1. The performance of
Fig. 12. Performance of detection in rectangular ROI areas using sobel operator for four different horizontal thresholds when vertical threshold is changed from 0.8 to 1 by an increment of 0.1.

Fig. 13. Performance of cost in rectangular ROI areas using sobel operator for four different horizontal thresholds when vertical threshold is changed from 0.8 to 1 by an increment of 0.1.

Fig. 14. Performance of proposed method for different ranks when horizontal thresholds is set to 0.97 and vertical threshold is changed from 0.8 to 1 by an increment of 0.1.

this evaluation is shown in Fig.14. When the false positive rate is 34%, the true positive rate is 100% for rank A and B, and 98% for rank C. The vertical threshold at this point is 0.96.

As we mentioned in 3.1, the automated system which is able to detect the rank A and B faults is acceptable for sewer pipe inspection. Supposing the false positive rate of 34%, we can attain the true positive rate of 100% by the proposed algorithm for the sewer pipe images. We showed this result to Water Environmental Section in Kitakyushu City. They also confirmed that the resulting detection by the proposed system is acceptable from a practical point of view. The reduction of time and cost in sewer inspection are also realized.

3.3 Detection in the Real World

To evaluate the performance of the proposed system in the real world, we use the prototype autonomous mobile robot, KANTARO, designed for inspecting sewer pipe net. It can move autonomously through 200-300mm diameter sewer pipes and also carry various sensors such as a camera and a 2D laser scanner.

The main difference between KANTARO and the conventional inspection equipment is that the former moves autonomously and also is able to turn at junctions in sewer pipes and to climb a step up to the height of 5cm. Fig.15 provides the overview of KANTARO.

The sewer images taken by KANTARO vision system are displayed in real time on a special designed Graphic User Interface(GUI). The user is able to control the fault detection module, the robot motion and navigation with the help of the GUI. Additional information such as edges and correlations are available to help experts analyze data.

The fault detection module operates when the robot inspects the sewer pipe net, and any notable faulty areas are marked and saved as a still image with location and time information in a report folder. Finally, this information can be printed and used for generating a report. Fig.16 illustrates an example of GUI detecting faulty areas by fault detection module during the inspection.

We evaluate the proposed system and KANTARO with designed GUI in the real sewer pipe net. The general information of inspection by using proposed system in real sewer pipe net is shown in Table 4.

Table 4 shows sewer pipes net of length of 32(m), 88(m) and 132(m) with 2, 4 and 6 manholes is inspected. The inspection time shown here depends on the speed of the robot.

The inspection results are shown in Table 5. Note that the inspected pipe net has been checked by sewer inspection company using the conventional system, therefore the numbers and locations of existing faults in each area were known in advance. The inspection results show
that all existing faults in sewer pipe net are detected by the proposed system. Also, for generating a final report, we only need to print the report folder images (each image has the location, time and marked faulty areas information). We can say that the proposed system succeeds in attaining high detection performance, time and cost reduction in sewer inspection. Fig.17 shows a scenery of inspection by proposed system in real sewer pipe net.

4. Conclusions

We have proposed an intelligent system for detecting faulty areas automatically and implemented it in a real time system to solve the “real-world” problems in civil robots. In contrast to the conventional manually operated systems, the proposed system can automatically detect faults and run in real time. Its detection performance is 100%, when the false positive rate is 34%. This ratio is acceptable for sewer inspection, and the reduction of time and cost is also realized.

Future work should aim at further decrease in the false positive rate by keeping high true positive and to find other superior techniques for fault detection.

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