Automated Inspection of Utility Pipes: A Solution Strategy for Data Management

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ABSTRACT: Rehabilitation of urban infrastructures has received considerable attention in North America, creating a need for automation. Automating the rehabilitation process of various infrastructure facilities is driven by the need for cost reduction, higher quality and improved safety. This paper describes an automated system, AUTO-DETECT, recently developed, for rehabilitation of sewer pipes. AUTO-DETECT automatically analyzes the CCTV videotapes that depict the conditions of the surveyed pipes and consequently detects and classifies defects. It introduces five sets of specialized neural networks, each is dedicated for one type of defect. The paper also presents the integration aspects of these five sets of neural networks to formulate a solution strategy that is utilized to improve the performance of the developed diagnostic system.

KEYWORDS: Automation; Sewer pipes; Inspection; Data management.

1. INTRODUCTION

Rehabilitation of urban infrastructures has received considerable attention in North America, creating a need for automation. Automating the rehabilitation process of various infrastructure facilities is driven by the need for cost reduction, higher quality and improved safety. A typical maintenance or rehabilitation process of underground sewer pipes usually starts by surveying these pipes and collecting relevant data about their condition. This data usually highlights many aspects and provides useful information such as the presence, type, number and location of defects. CCTV (closed circuit television) cameras are commonly used to capture these data. CCTV cameras produce a videotape that has to be visually inspected by a human expert in order to identify and locate defects, if they exist. The process is usually time consuming, tedious and expensive. Interviews conducted with several municipal engineers and consultants in Quebec and Ontario, Canada revealed that the cost of sewer inspection is about CDN \$1.5 per linear meter, 30 % of this cost (i.e. \$0.42) is spent on inspection of videotapes (Shehab-Eldeen 2001).

This paper describes an automated system, AUTO-DETECT, recently developed, for rehabilitation of sewer pipes (Shehab-Eldeen 2001). AUTO-DETECT automatically analyzes the CCTV videotapes that depict the conditions of the surveyed pipes and consequently detects and classifies defects. It utilizes image analysis techniques and artificial intelligence (AI) to perform its task through five sets of specialized neural networks, each set consists of three networks. Unlike the work developed earlier by the authors (Moselhi and Shehab-Eldeen 2000) where one classifier was developed to detect different types of defects, this paper introduces five sets of specialized neural networks, each is dedicated for one type of defect. This paper also presents the integration aspects of these five sets to formulate a solution strategy that employs a multiple classifier technology, designed to improve the performance of the developed system. An example application is presented to demonstrate the use and capabilities of the developed system.

2. DEVELOPED SYSTEM

The developed system makes use of and builds on current practice. The process used in current practice for detecting defects has been described elsewhere (Moselhi and Shehab-Eldeen 1999 (a) and (b)). Figure 1 depicts the overall configuration of AUTO-DETECT. As shown in this figure, a closed circuit television (CCTV), or a zooming, camera first scans the inner surface of a pipe and produces a videotape which is then played back using a VCR. The VCR then feeds the information captured on the tape to a computer equipped with a frame grabber and multiple classifier modules. The frame grabber captures and digitizes the frames of the acquired images. The multiple classifier module utilizes an image analysis software package to analyze those digitized frames and processes them in a manner so as to prepare a suitable input (i.e. feature vectors) to each classifier. A solution strategy is designed to integrate these classifiers (See Figure 2). The feature vectors are then fed into the developed system and are accordingly classified into five categories of defects. These categories are deposits, joint displacements, cross-sectional reductions, infiltration and cracks. This paper focuses primarily on the solution strategy module, other modules have been presented elsewhere (Moselhi and Shehab-Eldeen 2000 and 2001).

3. SOLUTION STRATEGY

Neural networks work in an analogous way to human experts. The more focused, i.e. domain specific, they are, the higher their problem solving capabilities. In order to express and demonstrate the importance of specialty in classification tasks, several classifiers (i.e. neural networks) were developed; each is considered suitable for a certain category of defects. This was considered advantageous, as opposed to one network that classifies more than one type of defect. Although diversity of networks is advantageous, it may lead to a problem in guiding the detected patterns to the proper channel so as to ensure that each category of defect is received by the most suitable specialized classifier. To overcome this problem a solution strategy is presented to organize data traffic so as to guide the patterns in an efficient manner and accordingly improve the performance of the system.

Figure 2 depicts the proposed solution strategy. As shown in this figure, all images are processed three times. In the first pass (i.e. inverted images), all images are inverted, dilated, background subtracted, thresholded, segmented and finally analyzed. In the second pass (i.e. non-edge detection), images are subjected to the same image processing techniques except for inversion. In the third pass (i.e. edge detection), all images are subjected to a number of operations such as background subtraction, edge detection, dilation, thresholding and analysis. The reason behind subjecting the same videotape to a number of passes is to benefit from all image processing techniques that are necessary to detect all categories of defects recognizable by the system.

As can be seen in Figure 2, patterns depicted on images subjected to the first pass (i.e. inverted images) will first be processed by set of networks number 1, specialized in classifying deposits. These networks will classify the input data (i.e. patterns) into two categories: “Deposits” and “Else” (i.e. non-deposits). All patterns classified as “Else” will be screened based on their X and Y coordinate and will be further processed by another two sets of networks (i.e. sets no.2 and 3), each is specialized to deal with a specific set of defects. Patterns with X and Y coordinates located only at the center of an image will be fed into the networks specialized in classifying cross-sectional reductions and misalignments (i.e. set no. 2 and 3, respectively). Patterns classified as “Else” by set # 2 and 3 will be ignored being either non defects or defects that are not recognizable by the system. It should be noted that the system recognizes more than 90% of defects that commonly exist in sewer pipes (Moselhi and Shehab-Eldeen 1999(b)).

Patterns depicted on images subjected to the second pass (i.e. non-edge detection) will be fed into the networks specialized in classifying infiltration (i.e. set no 4). These networks are capable of classifying patterns into two categories: “Infiltration” and “Else” (i.e. non-infiltration). It should be noted that all patterns classified as “Else” are considered as either non defects or defects that are not recognizable by the system.

Patterns depicted on images subjected to the third pass (i.e. edge detection) will be fed into the networks specialized in classifying cracks (i.e. set no 5). These networks are capable of classifying patterns into two categories: “Crack” and “Else” (i.e. non-crack). It should be noted that all patterns classified as “Else” are considered either non defects or defects that are not recognizable by the system. It should be noted that each of the five sets consists of three neural networks (Moselhi and Shehab-Eldeen 2001 and Shehab-Eldeen 2001).

4. EXAMPLE APPLICATION

To demonstrate the use of the developed system and the capabilities of its solution strategy module, the image shown in Figure 3 was considered. It should be noted that due to space limitations, the case example will focus primarily on the third pass (i.e. detection and classification of deposits using edge detection).

As can be seen, the image depicts a number of objects. These objects are cracks and a number of non-defects. To detect and classify these objects, the image was processed in the same manner as explained earlier. The image was segmented as shown in Figures 4. As can be noticed 15 objects were detected. The feature vectors describing these objects were then fed into two classifiers. The first is specialized in cracks, while the second was trained to classify four types of defects: (1) cracks; (2) multiple cracks; (3) cross-sectional reductions and (4) misalignments. The results obtained from the specialized and non-specialized classifiers are shown in Figure 5 and 6, respectively. As can be noticed that the specialized classifier reduced the false alarm for presence of cracks by 50%. Clearly this finding, while indicative of benefits of multiple specialized classifiers, can not be generalized.

5. CONCLUSION

An automated system for detection and classification of defects in sewer pipes has been presented. The system utilizes image analysis, solution strategy and multiple classifier modules to performing its task. To demonstrate the importance of specialty in classification tasks, several classifiers (i.e. neural networks) were used; each is considered suitable for a certain category of defects. These classifiers are specialized in deposits, cross-sectional reductions, misalignments, infiltration and cracks. The paper focused primarily on presenting a solution strategy that was developed to organize data traffic so as to guide the extracted feature vectors (i.e. signatures) of various defects to a set of specialized neural networks in an efficient manner. This was carried out in order to improve the overall performance of the developed system. This was considered advantageous, as opposed to one network that classifies more than one type of defect. A case example was also presented.

6. REFERENCES

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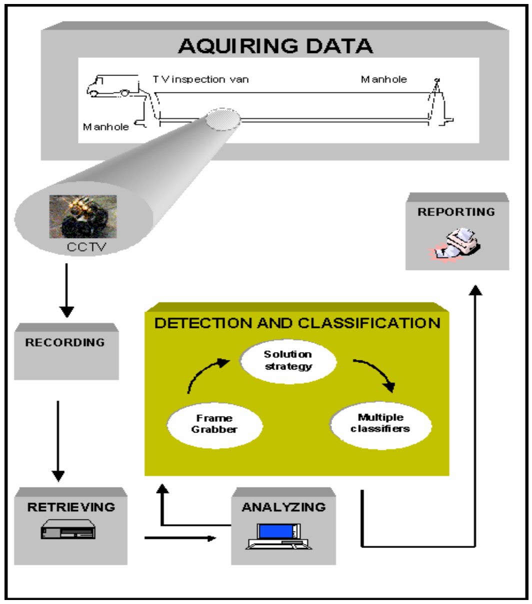

Figure 1: Developed Automated Detection and Classification System

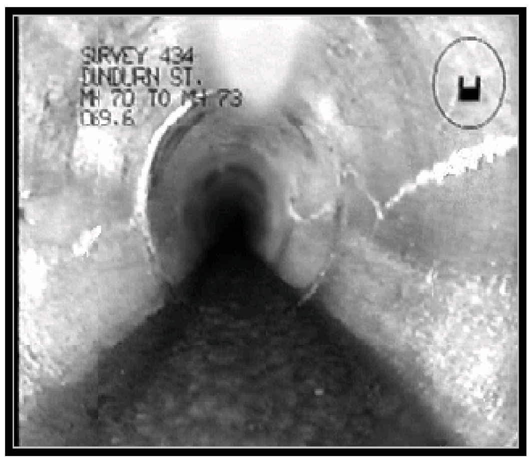

Figure 3: Original Image

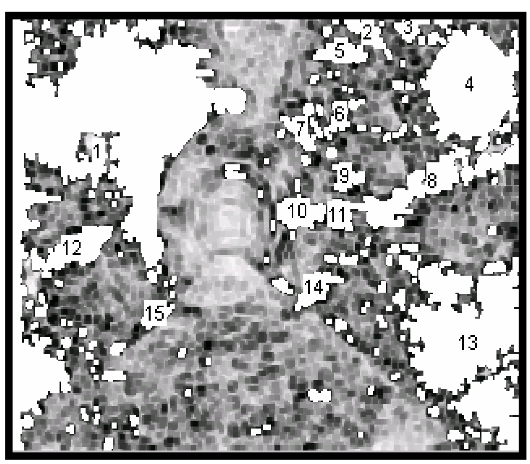

Figure 4: Segmented Image

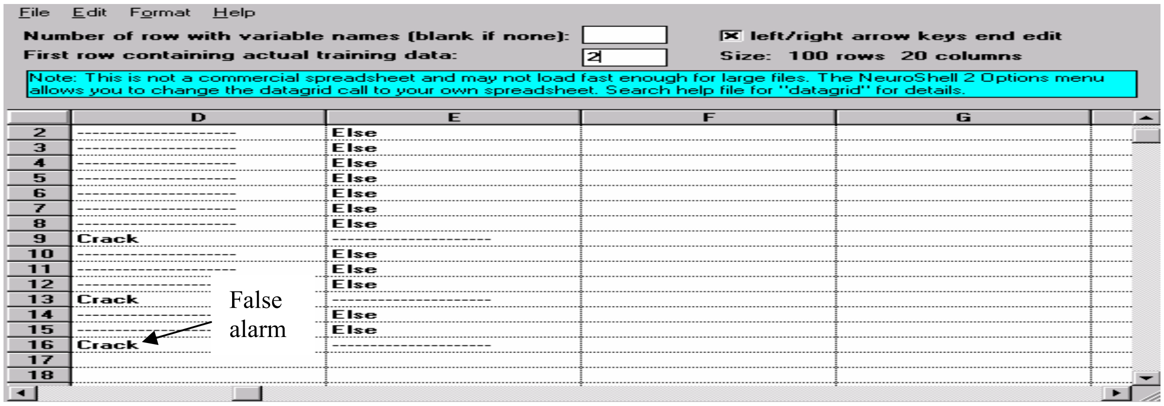

Figure 5: Results Obtained Form the Specialized Classifier

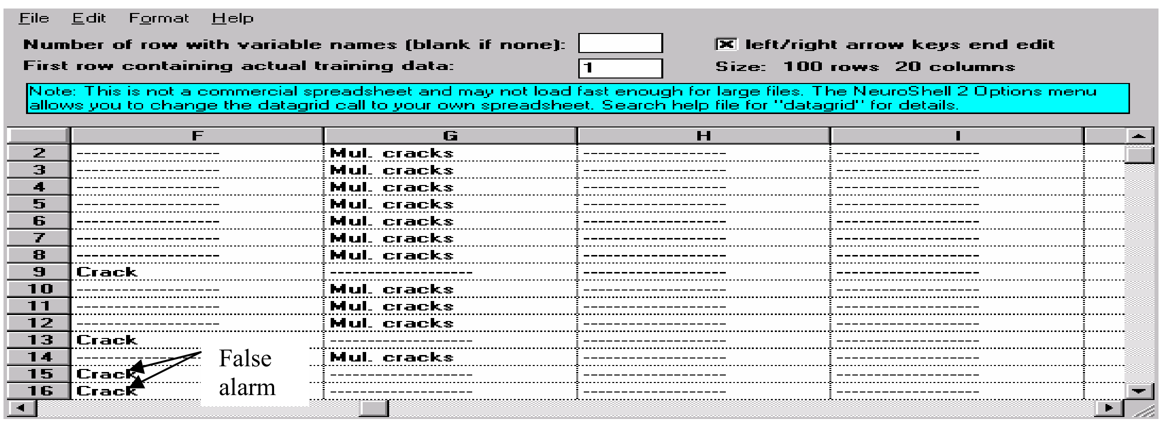

Figure 6: Results Obtained Form the Non-specialized Classifier

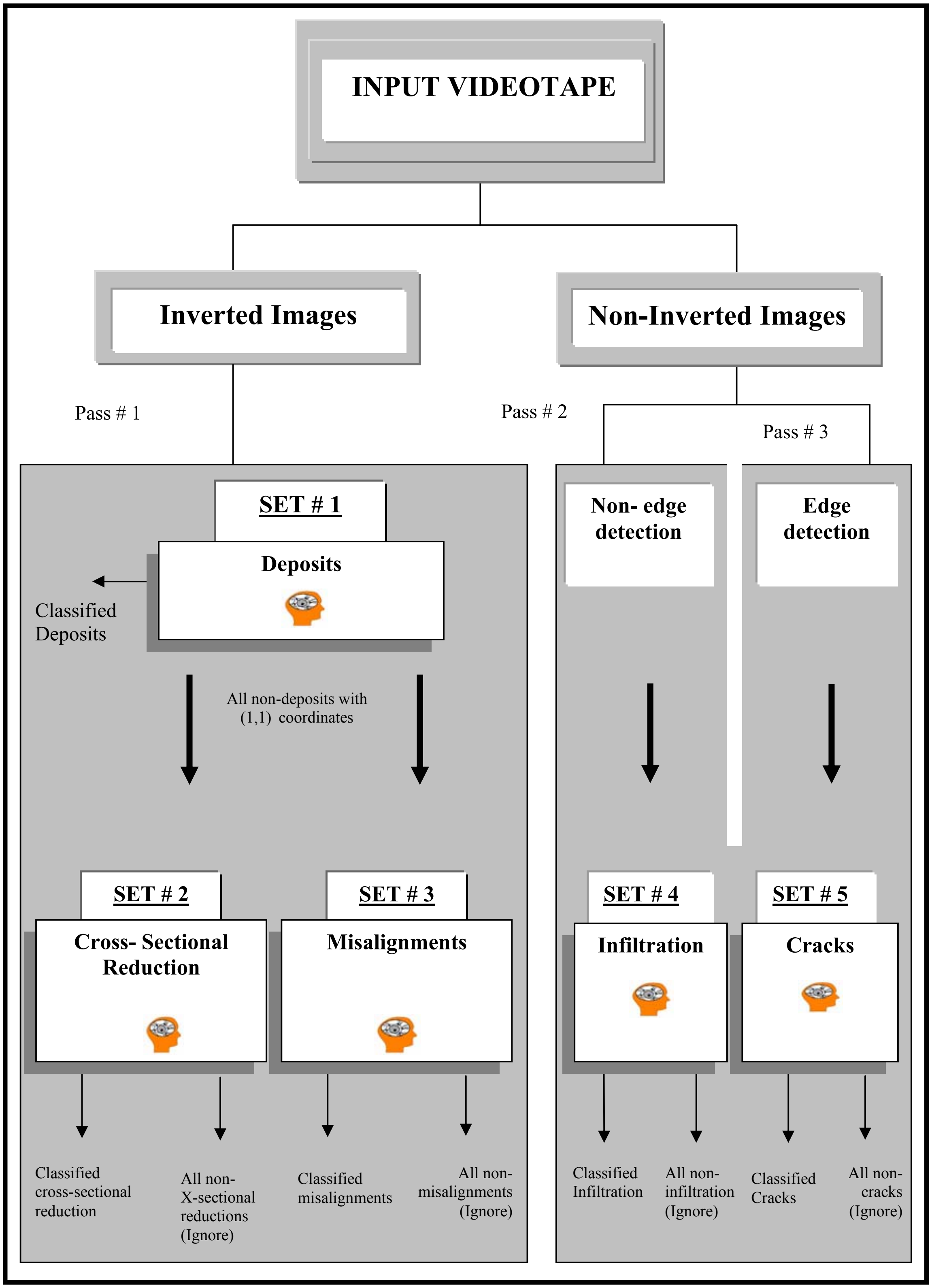

Figure 2: Solution Strategy