Neuro-Fuzzy Approaches for Sanitary Sewer Pipeline Condition Assessment

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Abstract: Recent advances in optical sensors and computing technologies have led to the development of inspection systems for underground facilities such as water lines, sewer pipes, and telecommunication conduits. It is now possible for inspection technologies that require no human entry into underground structures to be fully automated, from data acquisition to data analysis, and eventually to condition assessment. This paper describes the development of an automated data interpretation system for sanitary sewer pipelines. The interpretation system obtains optical data from the Sewer Scanner and Evaluation Technology (SSET), which is known to be the current leading-edge technology in inspecting sanitary sewer pipelines. The proposed system utilizes artificial neural networks to recognize various types of defects in sanitary sewer pipelines. The framework of this system includes modification of digital images for preprocessing, image feature segmentation, utilization of multiple neural networks for feature pattern recognition, and the fusion of multiple neural networks via the use of fuzzy logic systems.

INTRODUCTION

Several estimates claim that in the United States there are approximately 800,000 mi (1,280,000 km) of underground sewer lines that are owned and operated by over 17,000 separate sewerage authorities (Water 1994). Many of the nation's sewer systems are deteriorating, becoming more vulnerable to failure. Deteriorated sewer systems, like the one shown in Fig. 1, are time bombs, threatening to contaminate the ground water and soil, in addition to causing traffic disruptions, loss of property, and, in some cases, even loss of life.

Two primary challenges affect sewer rehabilitation. First, most rehabilitation work has to be done in heavily developed areas; second, this rehabilitation work is frequently performed only when major failure occurs. Rehabilitation is, then, difficult and costly (Water 1994). Hence, it is very important to have effective methods for assessing the condition of sewer lines in order to evaluate the level of deterioration, and for determining the mode and the frequency of rehabilitation that will be most cost-effective, while being less disruptive.

Many technologies have evolved over the past five years that have the potential for inspecting, monitoring, and evaluating infrastructure problems. However, the effective application of these technologies has been slow. This problem can be addressed in two steps.

1. The accuracies and precisions of these infrastructure inspection technologies must be analyzed in order to quantify the variances of various technologies (Maser 1988; Huston 1991).
2. Effective and speedy interpretation of the data provided by these technologies must be improved (Feng et al. 1995). A deeper understanding of the precision and relevance of the measurements taken by these technologies is a necessary input to the maintenance and rehabilitation strategy process, in order to incorporate the risk element into these decisions.

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Note. Discussion open until June 1, 2001. To extend the closing date one month, a written request must be filed with the ASCE Manager of Journals. The manuscript for this paper was submitted for review and possible publication on December 22, 1999. This paper is part of the ***Journal of Computing in Civil Engineering***, Vol. 15, No. 1, January, 2001. ©ASCE, ISSN 0887-3801/01/0001-0004–0014/$8.00 + $.50 per page. Paper No. 22089.

This paper describes the development of an improved methodology for accurately analyzing and interpreting data regarding the condition of sanitary sewer pipelines. The methodology involves the use of advanced data acquisition tools and a framework based on image processing and artificial neural networks. The advanced data acquisition tools provide high-quality digitized information to the automated assessment system through image preprocessing. The proposed system analyzes and assesses defects using image pattern recognition techniques.

ADVANCEMENTS IN CONDITION ASSESSMENT OF SEWER PIPELINES

Detection of interior defects is the first step in assessing the condition of sewer pipelines and developing rehabilitation strategies. Internal inspections are commonly performed through the following three methods: (1) physical inspection; (2) photographic inspection; and (3) closed-circuit television (CCTV) inspection. Physical inspection involves direct entry of personnel and is limited to inspection of larger sewers not in service. Photographic inspection utilizes a camera to take a series of color photographs along the inside of sewer lines. The present state-of-the-practice inspection technologies are dominated by CCTV technology, in which remotely controlled vehicles carry a television camera through the sewer pipes. Diagnosis of failures or defects depends on the experience and the capability and concentration of the operator, as well as the reliability of

FIG. 1. Deteriorated Masonry Sewer (Collins and Stude 1995)

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the television picture. Detection of subtle defects and assessment of the degree of deterioration are particularly error prone, so this method is adequate only for detecting gross defects.

Some promising nondestructive, diagnostic methods have recently been developed for condition assessment of sewer pipelines. These include the following: (1) infrared thermography systems that use temperature differentials between surfaces/elements (i.e., water leaks are determined by the existence of cooler surfaces, and voids are evidenced by a warmer signature in thermographic images); (2) sonic-distance measurement methods (i.e., pipe cracks under water or mud are identified by irregular signal responses from the objects); and (3) ground penetrating radar techniques that utilize the emission of short pulses of electromagnetic energy (Foillard et al. 1995). In these methods, the inspection process does not yield a complete picture of the condition of sewers due to the reliance on technology that depends on one mode of data collection.

To compensate for the shortcomings of the diagnostic methods noted previously, new systems such as the pipe inspection real-time assessment technique (PIRAT), KARO, and the sewer scanner and evaluation technology (SSET) have been developed. A German industry-research collaborative group developed the robot inspection system, KARO, to automatically detect the type, location, and size of defects in sewer lines. The objective of the KARO technology is to alert the operator of a possible defect by processing the signals in an intelligent way; however, the technology is yet to be proven

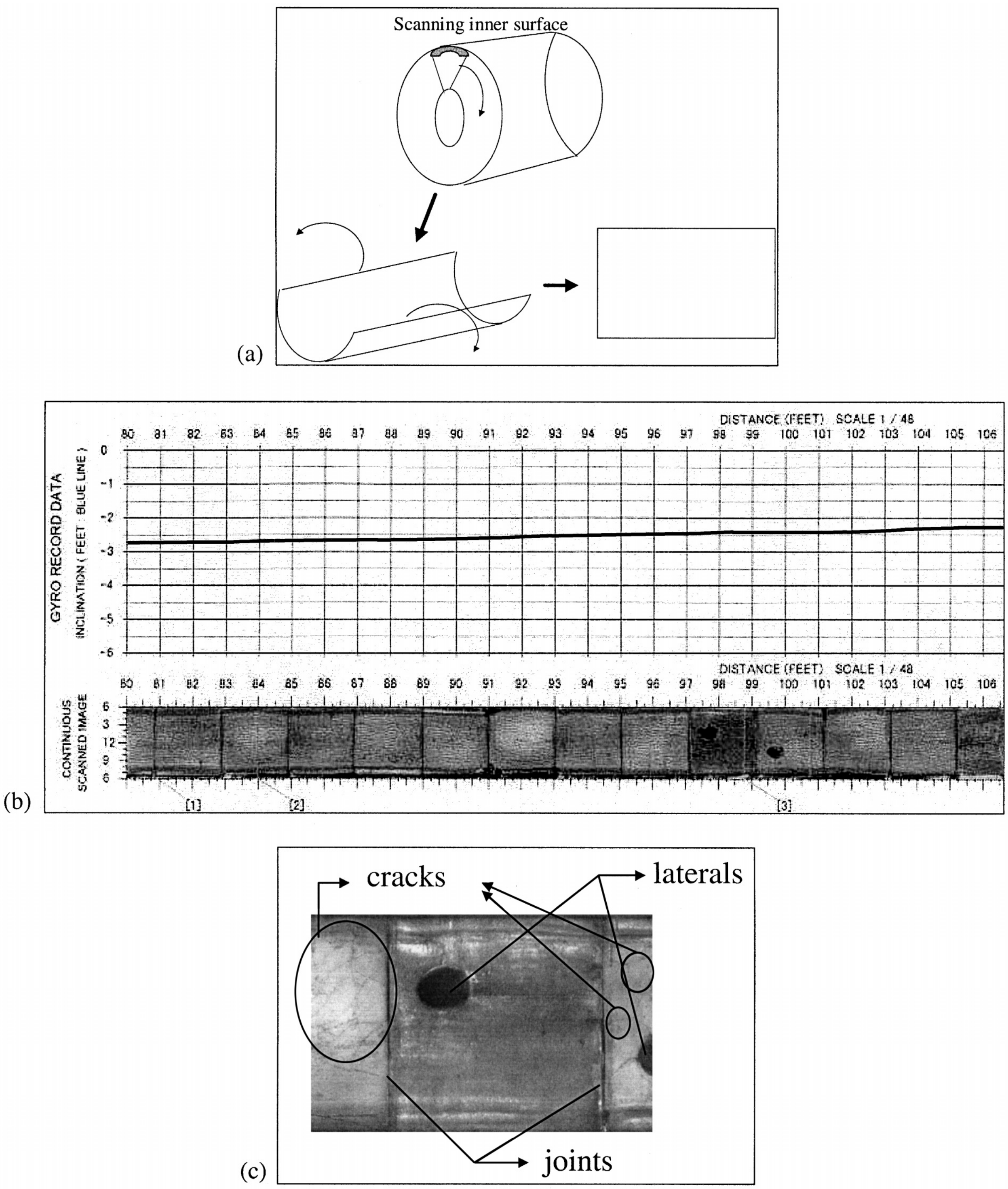

FIG. 2. View of: (a) SSET Scanning Inner Surface of Pipe; (b) Sample SSET Image along with Gyroscope Data; (c) Sample Enlarged Part with Defects

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(Commonwealth 1999). KARO is a remotely or semiautomatically controlled multisensory system based on a 3D optical sensor, ultrasonic sensors, and a microwave sensor (Kuntze et al. 1995). The Australian water authorities recognized the limitations of single-sensor CCTV operation and developed a new multisensing technology, named PIRAT (Campbell et al. 1995). A laser scanner is used in low-flow sewers or a sonar scanner is used in flooded sewers where the pipe surface is not visible. The in-pipe vehicle also carries a high-quality CCTV facility for navigation and for the production of a video record (Sharpe et al. 1995).

In Japan, the SSET was developed jointly by TOA Grout, CORE Corporation, and TGS Company. Higher-quality data regarding sewer conditions can be obtained by utilizing SSET's combination of CCTV technology, an optical scanner, and gyroscopic technology. The SSET provides a CCTV video record, a full-circumference scanned image of the pipe [Fig. 2(b)], a computer-generated color-coded printout of the defects, a written description of each defect along the pipe (based on inspector reports), and horizontal and vertical pipe deflections (Abraham et al. 1997; Iseley et al. 1997; Wirahadikusumah et al. 1997). This information provides the engineer the ability to see the total surface of the pipe from one end to the other. Another advantage of SSET is that it reduces the amount of fieldwork greatly. In the case of conventional CCTV inspection, the operator must stop the operation whenever the system encounters pipe defects, in order to record the defects. The SSET travels continuously while it collects the gyroscope data and the image data of the inner surface of the pipes [Fig. 2(a)]. The collected data are stored on a compact-disk read-only memory or a high-capacity disk that is delivered to the engineering office for the interpretation of the collected data and the assessment of pipe condition.

Asset managers of infrastructure systems rely on the accurate interpretation and assessment of condition data for decision making regarding future maintenance. Accurate assessment is crucial for astute life-cycle analysis of infrastructure systems. Although good inspection technologies exist, the reliability of condition assessment is low due to the subjective interpretation of images. There are some challenges in automating the interpretation of multisensory data. The task to be performed by the interpretation system is complex because there are many types of defects (e.g., leaking joints, cracks, root intrusions, corrosion, and so on). In addition, some of these defects may overlap.

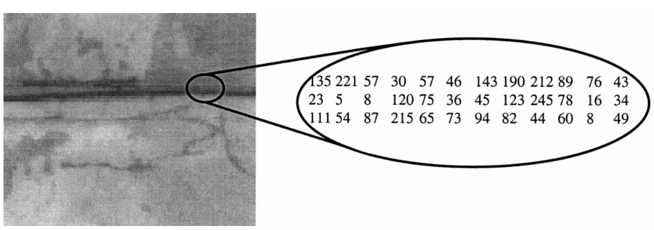

FIG. 3. Gray-Level Image of Inner Surface of Sewer Pipeline

CURRENT PRACTICES IN SANITARY SEWER INSPECTION

Advances in computer technology have accelerated the development of automated inspection of the sanitary sewer pipelines. Feature recognition basically uses techniques ranging from statistical methods, or the knowledge-based (or rule-based) artificial intelligence (AI) system, to artificial neural networks (ANNs). Combining two methods/technologies is becoming common. For example, the PIRAT system developed by the Commonwealth Scientific and Industrial Research Organization in Australia for commercial purposes uses a combination of the rule-based system and neural networks (Sharpe et al. 1995). The procedure involves (1) image preprocessing and segmentation utilizing the data obtained by PIRAT; (2) image classification using the feedforward neural network; and (3) interpretation using AI tools.

Sinha et al. (1999) utilize a statistical approach for the fusion of the results from two crack detectors for feature recognition. The two detectors utilize different approaches for crack detection, so the detection results are independent of each other. One detector may recognize a certain crack and the other may not. The use of two detectors may lead to better results if the method of fusion is appropriate for the specific problem, such as crack detection. The following sections discuss the types of digital images and their modifications, and the key features of artificial neural networks with respect to their applicability for infrastructure assessment of sewer data.

Image Preprocessing in Spatial Domain

Appropriate preprocessing is a very important step to make images suitable for various purposes. For example, an image can be preprocessed to make it distinguishable to the human eye and/or more appropriate for computing purposes. The processing does not create new information from the original information. It sharpens the image feature, adjusts contrast, and so forth (Bow 1992).

Gray-Level Images

When digitized images are obtained from an image scanning device (in this case, SSET scans the inner surface of the sanitary sewer pipes), 24-bit true color images are produced. These digitized images are either color images or black-and-white images. Image data are stored in the form of matrices, in which elements represent pixels of the image. A gray-level image (usually called a black-and-white image, and sometimes called an intensity image) has only one matrix. Each element

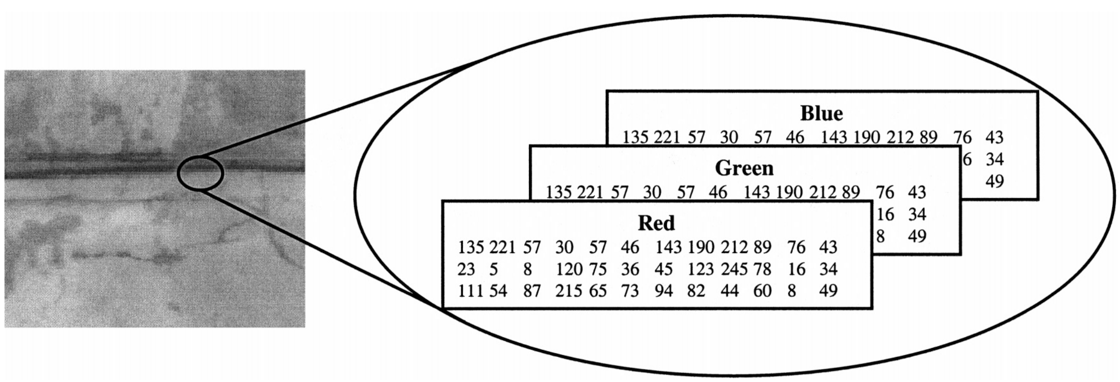

FIG. 4. RGB Image of Inner Surface of Sewer Pipeline

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of the matrix represents the gray level (degree of darkness or brightness) in each pixel on the screen or printed output. When a gray-level image has an eight-bit level, each pixel has a value that ranges from zero darkness to a 256 (2^8) darkness value. Fig. 3 shows how a gray-level image is represented in matrix format (*Image* 1998).

Red/Green/Blue (RGB) Images

An RGB image is a color image. Colors are described in three basic color components—red, green, and blue; hence, the name is RGB. RGB images are also represented in matrix form. For an RGB image, three layers of matrices are required. Thus, each pixel has three values of red, green, and blue. When an image has 24-bit color depth, each color component has an eight-bit level. Many different colors can be represented through a combination of the three layers of the eight-bit level. A 24-bit RGB image, obtained from SSET output, can have 16,777,216 (2^{24}) different colors. Fig. 4 shows an RGB image that is represented in the form of a three-layer matrix.

An RGB image can be converted into a gray-level image by dropping color information. For example, by averaging three matrices, one gray-level matrix can be produced (Fig. 5). In the suggested assessment system, RGB images from SSET are converted into gray-level images in the first step of preprocessing. This enables gray-scale modification and edge-detecting operations.

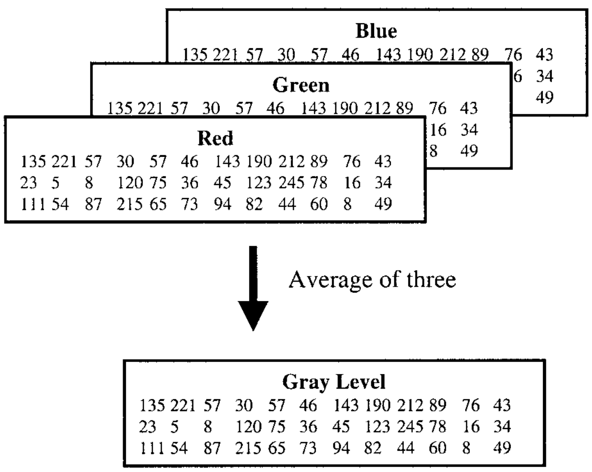

FIG. 5. Conversion of RGB into Gray-Level Image

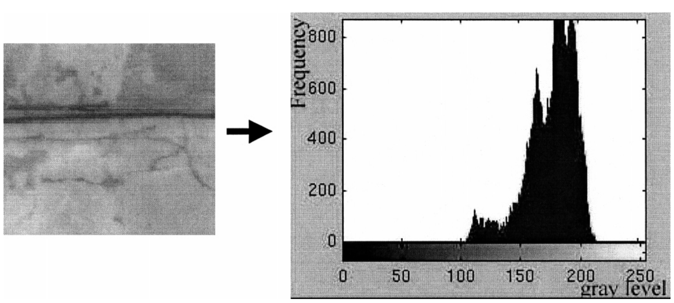

FIG. 6. Histogram of Gray-Level Image

Histogram and Its Modification

The gray-level histogram gives the intensity of a gray-level image without the location information. For an image $f(x, y)$ with a discrete gray-level range $\{0, 1, 2, \ldots, 255\}$, the gray-level histogram $H(z)$ is the discrete graph plotted with the number of pixels at gray level z versus z, or

$$H(z) = \int\int [f(x, y) = z]\, dx\, dy \quad \text{(Bow 1992)} \tag{1}$$

Fig. 6 shows a histogram of a gray-level image. The horizontal axis presents the gray-level intensity (z) of the gray-level image, and the vertical axis represents frequency $[H(z)]$.

One of the most useful methods for extracting a feature of interest from an image is to perform the binary transformation of a gray-level image through thresholding. Through binary transformation, the image is represented with only two different values—one or zero. For example, if the image in Fig. 6 is binarized at a gray level of 150, all the pixels having a level greater than 150 will be assigned 255 (maximum value for an eight-bit gray-level digital image); the others will be assigned 0. Thus, the binary image has only two values, and it is a pure black-and-white image without any intermediate gray level. Fig. 7 shows an example of binary transformation. A vertical line in the histogram shows the threshold value, and it divides the gray level into two levels of intensity (either black or white). Thus, the binary image can be represented as a matrix in which elements are either zero or one.

Edge Detection

Using an edge enhancement algorithm, an original image is modified into a new image that has amplified edges. Thus, edge detection ‘‘has the effect of making edges easier for the viewer to see, consequently making the image appear sharper’’ (Russ 1992). The main idea behind using these algorithms is to find large contrasts in the image. The algorithm can be processed using the following concept equations.

For a two-dimensional image $f(x, y)$, a vector gradient $\mathbf{G}[f(x, y)]$ can be defined as follows:

$$\mathbf{G}[f(x, y)] = \begin{vmatrix} \dfrac{\partial f}{\partial x} \\ \dfrac{\partial f}{\partial y} \end{vmatrix} \quad \text{(Bow 1992)} \tag{2}$$

The magnitude of this vector is

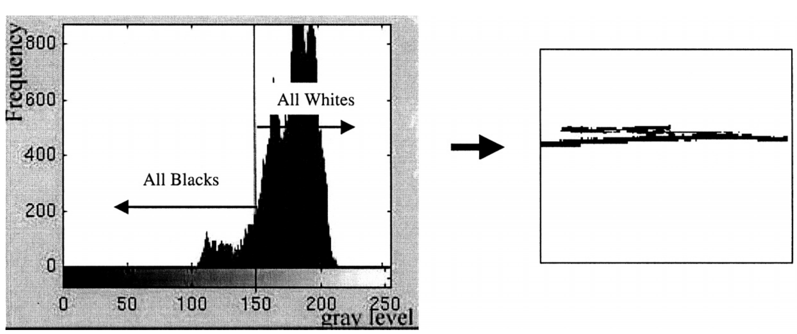

FIG. 7. Binary Transformation

$$\mathbf{G} = \left[\left(\frac{\partial f}{\partial x} \right)^2 + \left(\frac{\partial f}{\partial y} \right)^2 \right]^{1/2} \quad \text{(Bow 1992)} \qquad (3)$$

Eq. (3) can be written in a simplified form [(4)] to describe the role of the different elements in the image matrix

$$\mathbf{G} = \{[f(j, k) - f(j + 1, k)]^2 + [f(j, k) - f(j, k + 1)]^2\}^{1/2} \quad \text{(Bow 1992)} \qquad (4)$$

where (j, k) = certain point of an image or an element in the image matrix. Eq. (4) is called a three-point gradient (Bow 1992).

Thus, the gradient represents the rate of change of gray level in an image. The gradient is large when the brightness changes quickly, and is small for smooth areas. Fig. 8 shows only edges where the gradient is the maximum.

Artificial Neural Networks

ANNs are utilized for image recognition and assessment of condition. Neural networks consist of a large number of neurons or simple processing units. Each input applied to the ANN is multiplied by a corresponding weight. The weighted inputs are summed to determine the activation level of the neuron. The weights represent the knowledge in the system. Information processing takes place through the interaction among these units. The net input is then processed by an activation function to produce the neuron's output sign.

There are two learning methods used by neural networks—namely, supervised learning and unsupervised learning. Since sets of target data and data related to sewer pipes (in the form of SSET images) are available, the supervised learning method is appropriate for the sewer condition assessment problem. In this case, the supervised learning method with a back-propagation algorithm is used for simplicity. Fig. 9 describes conceptually a neural network employing the supervised learning method using a back-propagation algorithm for the training phase. Initially, input/output data sets and a neural network with random weights should be ready for training. When the first data set is input into the network, the network produces an output set that is far from the desired output. This output set is compared with the desired output set and the training algorithm adjusts the weights in the network in order to produce the desired output. This task is done iteratively for all of the data sets until the network produces output sets that closely mirror the desired output sets. When the network can produce outputs that match the desired outputs, the network is trained. The trained network is able to simulate new outputs from new input data sets if the input/output patterns are similar to those used for training.

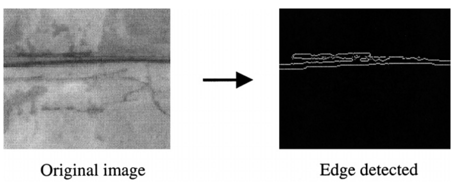

FIG. 8. Edge Detection

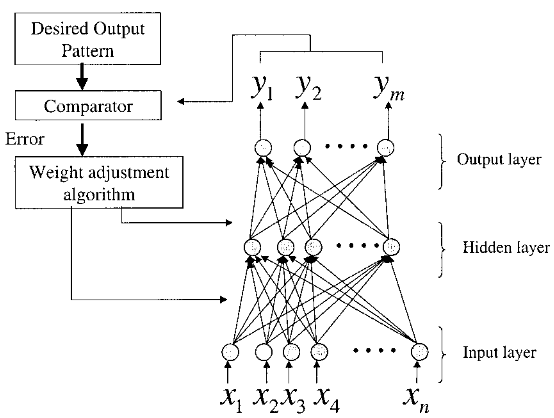

FIG. 9. Neural Network with Supervised Learning (Tsoukalas and Uhrig 1997)

Image Mapping and Recognition Using Artificial Neural Networks

Artificial neural network systems have learning and recall features; i.e., the networks have memory-like functions. Information is stored in the form of weights in the neural network. Because all weights are distributed over the network, the stored information is distributed over the network. Thus, a single incorrect weight may not affect the output values of the neural network. This structural fact enables the neural network to possess fault-tolerant memory. Since all of the image data points (especially in the case of the SSET images) have certain amounts of noise and undesired information, neural networks are good tools for image recognition.

AUTOMATED INTERPRETATION OF CONDITION DATA

The development of the automated interpretation system using artificial neural networks is divided into four steps—namely, image acquisition, preprocessing, defect recognition using multiple neural networks, and estimation of overall condition using fuzzy consolidation, as shown in Fig. 10.

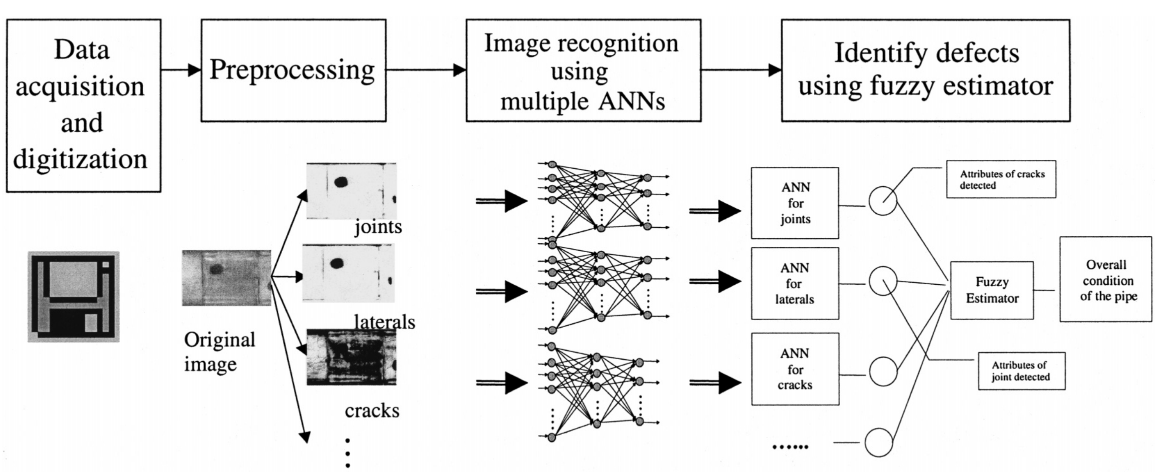

FIG. 10. Image Analysis and Recognition Using ANN

Step 1—Image Acquisition

Images of the inner wall of the pipeline are acquired (from CCTV and SSET). The images are digitized into three-layer, two-dimensional matrices, in which each row and column identifies a point in the image and the corresponding matrix element value represents the gray level at each layer. Each layer represents red, green, and blue, which are the basic color components for the color image. Each pixel in such a digitized array has a 24-bit color depth, which can store up to 16,777,216 (2^{24}) different colors.

Step 2—Preprocessing

The main purpose of preprocessing is to modify the original image into subelements/subimages that can be handled with greater ease. Preprocessing of the image entails early vision processing or low-level processing (Kulkarni 1994).

ANNs can handle original images to recognize the defects without the intermediate preprocessing steps. However, in this case, the size of the input data is very large—(24-bit color depth) times 638 × 1,000 (the size of the input image). This requires a very large number of input nodes in the ANN, which translates to high computational times. To reduce computational times, some modification of the original images is needed.

Through filtering, gray-scale thresholding, isolation of regions, edge enhancement, etc., the acquired images are treated in order to make them amenable for treatment by artificial neural networks. The original image is divided into several subimages and treated so that each subimage shows one type of defect (joints, laterals, cracks, etc.), as shown in Fig. 11. The defects of a certain type of pipe have different characteristics. To emphasize the defect types of interest, different methods of preprocessing were performed to produce multiple subimages to be fed to multiple neural networks. The input image data are converted into binary format so that it is easier to ''program'' the network, and faster computer processing speed is expected.

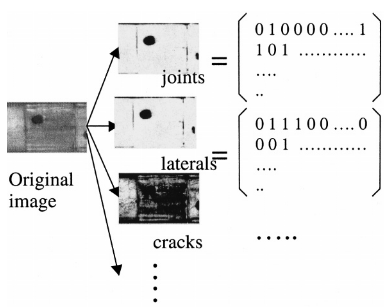

FIG. 11. Isolation of Defects

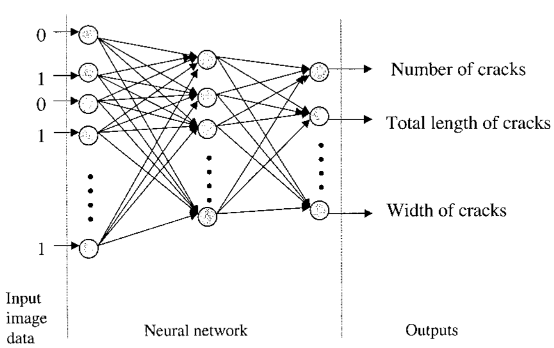

FIG. 12. Example: ANN for Crack Recognition

Step 3—Defects Recognition Using Multiple Artificial Neural Networks

After the images are preprocessed, multiple ANNs are used to recognize the type and level of the defects in the pipeline (Fig. 12). There are some advantages in using multiple neural networks and subdivided images over using a single input and one network. Theoretically, using one type of preprocessing and one neural network may solve the defect recognition problem. However, the size of the neural network will be very large, leading to long computational times. When the network is large, it is difficult to ''tune'' the network to improve accuracy by adjusting the structure of the network to test the correlations of input and output vectors. By dividing one large network into smaller networks, these problems may be reduced. Thus, using multiple subdivided images and multiple neural networks is an efficient way of solving the current problem.

A network is ''created'' for each type of defect as shown in Fig. 13. The outputs of a network are the attributes of a defect. For example, ANN 1 is developed for detecting joints and ANN 2 is developed for detecting corrosion. The input to the ANN for crack recognition would be the preprocessed image data, and the set of outputs would ''display'' attributes of cracks, such as the number of cracks, the total length of the cracks, the width of the cracks, and so on (Fig. 12). In the same manner, the attributes of joints may be defined as the number of joints in the projected section, the nature of the joints, and likewise. Table 1 shows an example of the attributes that can be used to define different defects.

The number of neurons in the input layer is dependent on the size of the input image data, and the number of neurons in the output layer is the number of attributes for each defect. The number of neurons in the hidden layer should be chosen by experimentation. Too many neurons in the hidden layer

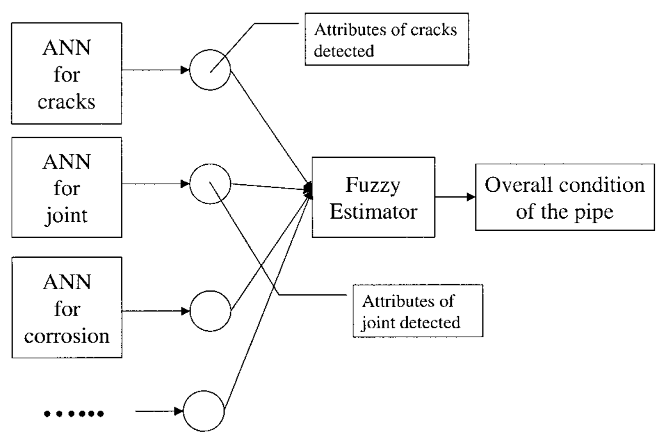

FIG. 13. Fuzzy Approach for Rating of Defects

TABLE 1. Example Attributes of Defects

Defects (1)	Attributes (2)
Cracks	Number of cracks
Cracks	Average width
Cracks	Maximum width
Cracks	Ratio (axial/lateral direction)
Cracks	Number of cracks extending from pipe joint
Lateral	Current size/original size
Lateral	Shape factor of lateral
Joints	Pipe joint in processed area
Joints	Thickness
Joints	Existence of cracks around joint
Joints	Condition
Roots	Size
Roots	Percent loss of cross-sectional area

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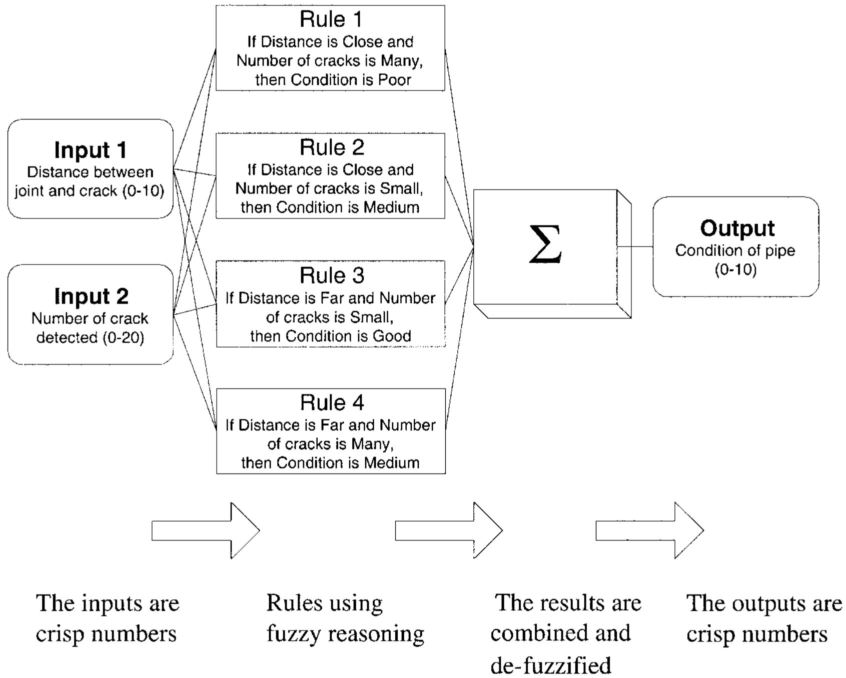

FIG. 14. Concept of Fuzzy Inference (*Fuzzy* 1998)

would result in slow computational speed without substantially increasing the accuracy.

In the supervised learning method, target values should be set for the training of an ANN. Target values are the known attributes of a defect. The ANN is trained with the known target values. This means that the outputs of a network, which are attributes of a defect, are compared with the target values and the network is trained by adjusting the weight factors in the network. As a network is trained, outputs tend to be ''close'' to the target values. Once the networks are trained, they are tested and verified with known defects, and they are ready to be used with the newly scanned data.

Step 4—Fuzzy Estimation Techniques for Pipe Condition Assessment

Fuzzy inference rules enable the modeling of uncertainty associated with vagueness, imprecision, and/or lack of information regarding a particular element of the problem at hand (Ross 1995). The attempt to develop automated interpretation for sewer pipeline assessment exhibits similar problem characteristics because the outputs from the neural network system have certain levels of imperfections. The proposed interpretation system implements fuzzy set theory and fuzzy implication techniques to automatically identify, classify, and rate pipe defects while minimizing the errors from the neural network system. This fuzzy estimator gives the outputs of the network some meaningful way to be interpreted and helps in describing the overall condition of the inspected pipe (Figs. 13 and 14). The major advantage of using the fuzzy system is that instead of sharp switching between modes based on breakpoints, the outputs can glide smoothly from regions where the system's behavior is dominated by either one rule or another (*Fuzzy* 1998; *Image* 1998).

RESULTS FROM PROTOTYPE

The proposed assessment methodology was applied and validated using SSET data from the sanitary sewer infrastructure in the city of San Jose, California. Twenty image files were randomly chosen out of 192 files to train the network (Fig. 15). The pipe material was clay.

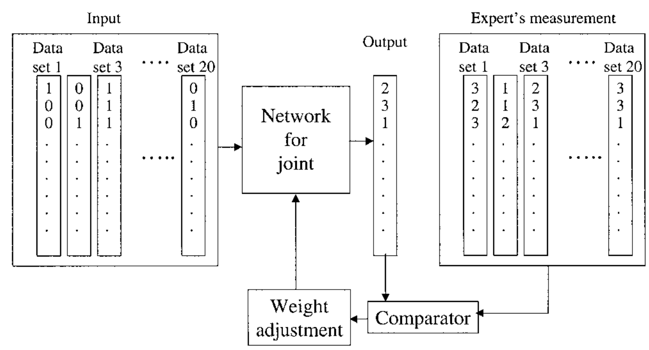

FIG. 15. Training Network

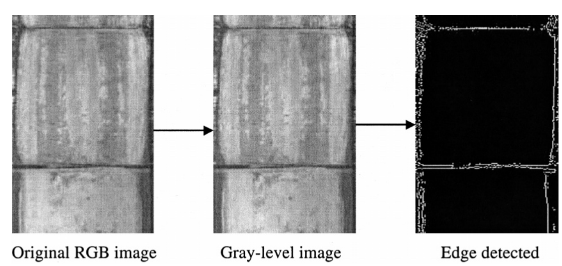

FIG. 16. Preprocessing of Image

Preprocessing

The original image from SSET is modified as shown in Fig. 16. The original color image was changed into a gray-level image and binarized through binary transformation in order to filter out the background noise. Then the transformed image was converted into an edge-detected image through the edge detection algorithm of Matlab version 5. The 638 × 1,000 image size requires 638,000 neurons in the input layer. The original image was reduced by one-quarter of the original image size to increase the computational speed and to avoid the restrictions of system memory. The data are ''fed'' to the neural network in the form of 159 × 250 size binary images.

Designing and Training Network for Pipe Joint Detection

When the preprocessing is completed, the edge detected binary image becomes the input to the trained neural network. Several attributes are assumed in order to describe the condition of the pipe joint. These attributes are characteristics of the pipe joint. In this research, the attributes are assumed subjectively because the main purpose of this neural network model is to test whether or not the network is capable of pipe joint pattern recognition. Once the network is structured, it is a relatively simple task to add or remove some attributes.

Suggested attributes of pipe joints are listed on the right side of Fig. 17. For instance, since a single image file of the original SSET data has at most two pipe joints, the values of the number of joints range from zero to two. Also, the condition of the joint could be assumed at three levels (poor, medium, good) as an example. If the target values have more levels (such as from one to 10), the network output reflects the variation automatically. Cracks near joints may cause more serious leakage than might ordinary cracks, so the feature to detect cracks near joints is attached. In addition to this, there is an independent neural network designed for crack detection. Thus, the results from the crack detector and joint detector will have redundant information. This redundancy is beneficial to improve accuracy when two or more neural networks are combined.

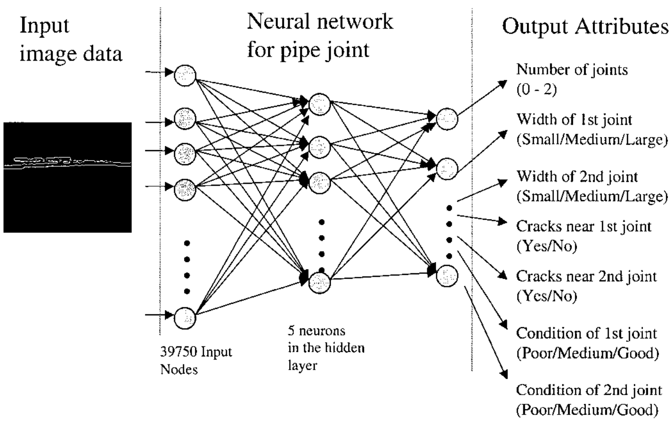

FIG. 17. Output Attributes of ANN for Joint Detection

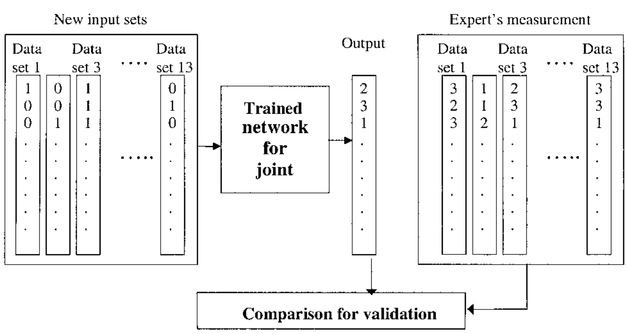

FIG. 18. Validation of Trained Network

A feedforward neural network with a back-propagation algorithm was used in the validation. There are 39,750 (159 $\times$ 250) neurons in the input layer. In the hidden layer, there are five neurons. There is no specific rule regarding the choice of the number of neurons in the hidden layer. Twenty image files were utilized to train the network (Fig. 15). While training the network, target values suggested by only one expert are used. This leads to more consistent outputs for defect recognition, ensuring consistency in the condition assessment of the pipes.

Neural networks should be first trained to predict appropriate answers. During the training session, expert knowledge is required. Typically, the expert will be the person who is a decision maker regarding the condition of the pipe. Because neural networks mimic the expert's knowledge from the input/output data sets, the expert should be assigned to the specific project, so that he/she can provide sample assessments that would be supplied to the neural network for the training data sets. Once the network is trained, the automated system performs assessment using the remainder of the SSET data.

Validation of Joint Detection Neural Network

By comparing the network outputs with the expert's measurements, the accuracy of the neural network system can be validated. Fig. 18 shows the diagram of the validation process. Thirteen randomly chosen images were used to test the accuracy of the system. The outputs from the neural network along with the expert's values are listed in Table 2.

This comparison shows a strong potential for effectively using ANNs for condition assessment of sanitary sewer pipes. For example, in the second image, there are two pipe joints.

TABLE 2. Outputs of Automated Assessment System (Expert Assessments Shown in Parentheses)

Image number (1)	Number of joints (2)	Width (first joint) (3)	Width (second joint) (4)	Cracks (Y/N)[b] (1/0) (first joint) (5)	Cracks (Y/N)[b] (1/0) (second joint) (6)	Condition (first joint) (7)	Condition (second joint) (8)
1	1 (1)	2 (1)	—[a]	N (N)	—[a]	3 (3)	—[a]
2	2 (2)	1 (2)	2 (2)	N (N)	Y (Y)	3 (3)	2 (2)
3	2 (2)	2 (2)	2 (2)	N (N)	N (N)	3 (3)	3 (3)
4	1 (1)	2 (2)	—[a]	N (N)	—[a]	3 (3)	—[a]
5	2 (2)	2 (2)	2 (2)	N (Y)	N (N)	3 (3)	3 (3)
6	1 (1)	2 (2)	—[a]	N (N)	—[a]	2 (1)	—[a]
7	1 (1)	2 (1)	—[a]	N (Y)	—[a]	2 (1)	—[a]
8	2 (2)	2 (2)	2 (2)	N (Y)	N (Y)	3 (2)	2 (2)
9	1 (1)	2 (2)	—[a]	N (N)	—[a]	0 (3)	—[a]
10	2 (2)	2 (2)	2 (1)	N (N)	N (N)	3 (3)	3 (3)
11	2 (2)	2 (1)	2 (2)	N (N)	N (N)	3 (3)	3 (3)
12	1 (1)	1 (1)	0 (0)	N (N)	Y (N)	2 (3)	0 (0)
13	2 (2)	2 (2)	2 (3)	Y (N)	N (N)	2 (3)	2 (2)
[Ratio of correct answers]	13/13	13/13	6/8	9/13	6/8	8/13	8/8

Note: Percentage of overall correct answers = 83%, percentage of correct answers regarding joint condition and width = 84%, percentage of correct answers regarding number of pipe joints = 100% (accuracy of joint detection), and percentage of correct answers regarding cracks = 72% (accuracy of crack detection).

[a]Second pipe joint is not available.

[b]Y and N refer to "yes" and "no."

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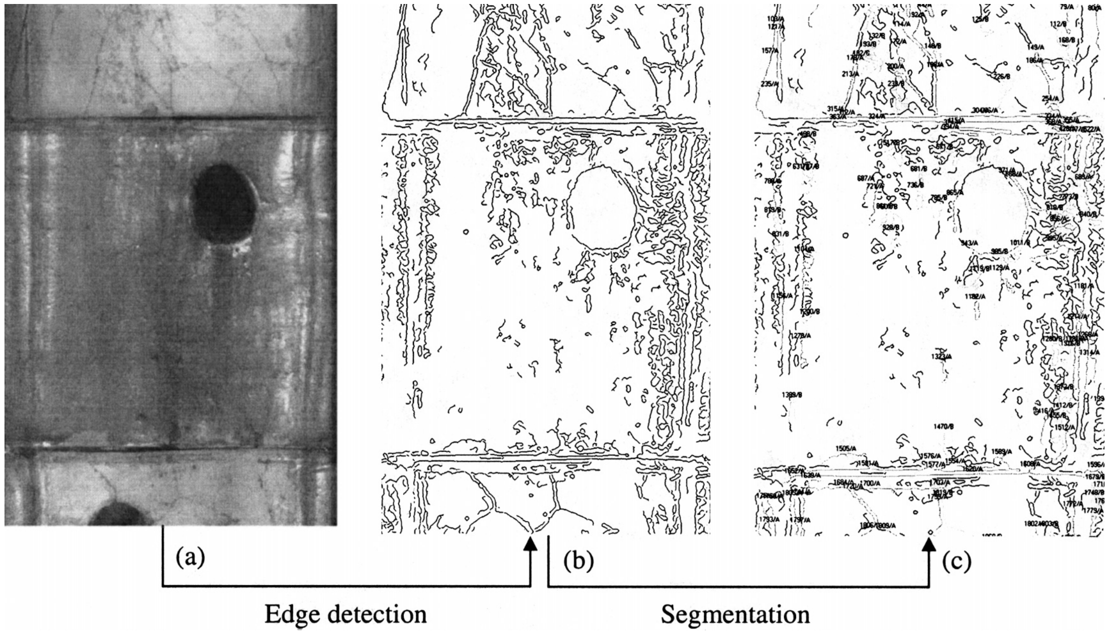

FIG. 19. Image Segmentation

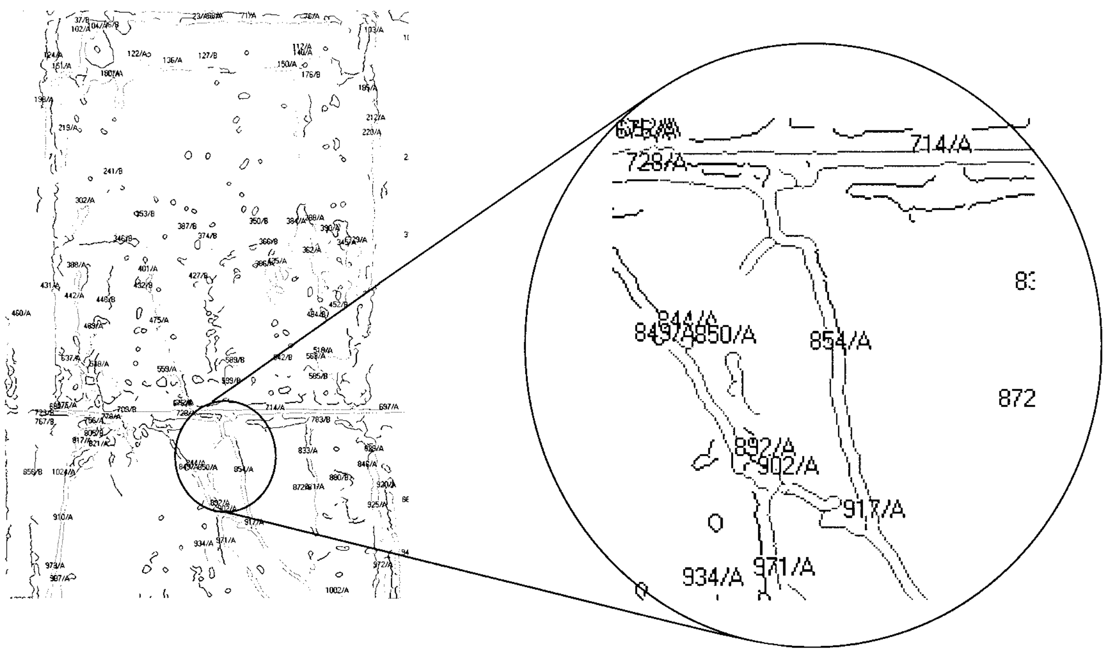

FIG. 20. Image Segmentation—Magnified

The first one has medium width (assigned a 2 for medium width; Table 2); the second one has medium width, as well. In the expert's opinion, there was a crack near the second joint (zero and one in the columns showing crack attributes) and the condition of those joints was rated as good (assigned a 3) for the first joint and medium (assigned a 2) for the second joint. As shown in Table 2, the system detected two joints in image number 2. The proposed assessment system detected 83% of defects accurately, as reflected in Table 2. The ANN also detected the existence of pipe joints with 100% accuracy. The conditions of joints were predicted with 84% accuracy.

Development of Crack Detection Neural Network

In the case of pipe joint detection, joints are easily separated from background noise because joints have unique characteristics. For example, if segmented features are long in the horizontal direction and they appear repetitively at constant distances, they are most likely pipe joints rather than cracks. In addition to these prominent characteristics, joints are easily separated during binary transformation, such as the thresholding process. However, cracks are not easily separated during binary thresholding; they appear similar to noise that is captured during the image acquisition stage. As a result, the isolated subimage for crack detection has noise (false information) mixed with the cracks (true information). Thus, the separation of cracks from noise is the key for developing the neural network for crack detection.

Once the original image is segmented and numbered as shown in Figs. 19 and 20, possible characteristics such as length, width, angle, moment of inertia, center of gravity, etc. are analyzed and extracted to find certain patterns that are unique to cracks or to noise. The extracted features are utilized to separate cracks from noise through a feedforward neural

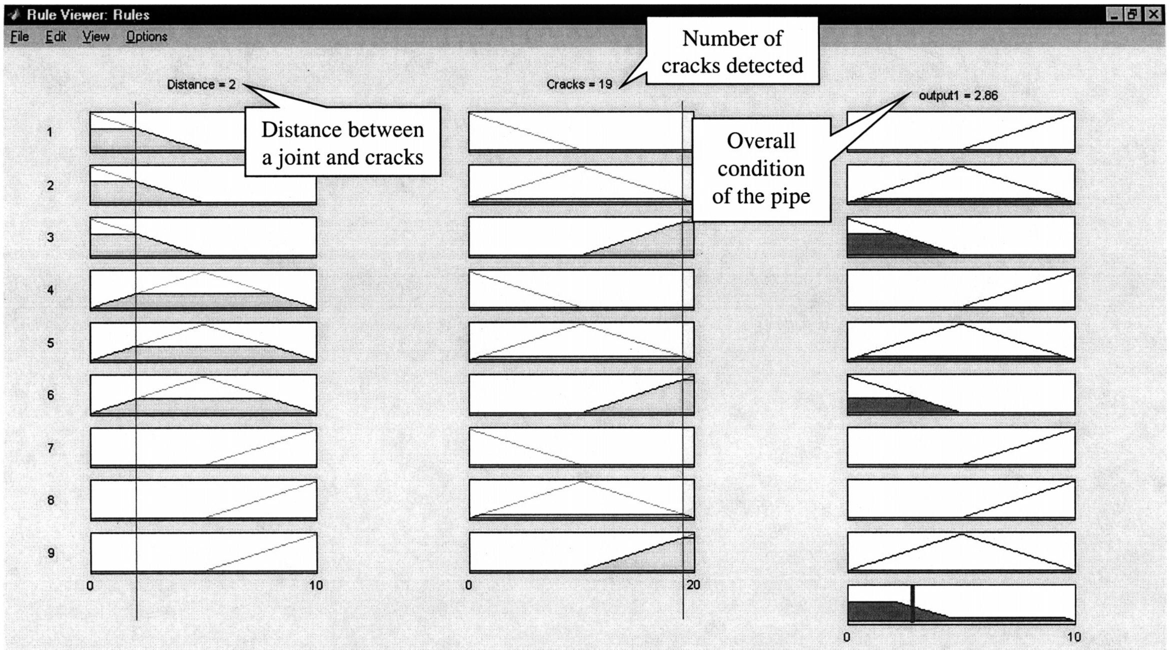

FIG. 21. Fuzzy Operation

network. While the segmented image is directly fed to the neural network for joint detection, for crack detection the characteristics of segmented features such as length, angle, area, etc. form the input data sets.

Building Fuzzy Consolidation System

Results from multiple neural networks are consolidated using a fuzzy algorithm. In the prototype interpretation system, the algorithm fuses the results of the joint detection ANN and the crack detection ANN. However, the outputs from the neural network have certain degrees of uncertainty. Variances exist between the true values (of the defects) and the output of the individual ANNs due to incomplete training sets, inaccurate and inconsistent input/target data sets, insufficient number of training loops, and likewise. These variances cannot be reduced by using fuzzy sets, but they can be appropriately handled to produce more accurate condition assessment (Fig. 14).

A fuzzy set is a set without a crisp or clearly defined boundary. It can contain elements with only partial degrees of membership. The first step is to take the inputs (in this case, the outputs from neural networks) to the fuzzy sets via membership functions. Then a fuzzy operator is applied, and outputs are aggregated and defuzzified. For example, if the distance between a joint and a crack is 2 (on a scale of 0–10, where 10 signifies a large distance) and the number of cracks detected is 19 (on a scale of 0–20, where 20 is the maximum number of cracks in a pipe section), then the fuzzy system may describe the condition of the pipe as 2.86 (on a scale of 0–10, where 1 signifies a pipe in severe structural condition). The resulting value (2.86) is the overall assessment using the fuzzy consolidator (Fig. 21).

TOOLS USED FOR DEVELOPMENT OF SYSTEM

The following tools were used for the development of the system: Matrox Inspector for image segmentation, Matlab for edge detection, and Microsoft Excel for segmented data handling. The process was performed manually; i.e., data from one software package were manually input to another. A linkage program that transfers data from one software package to another will be developed to improve the utility of the assessment framework.

SUMMARY

In this paper, sample data from San Jose were used to test the applicability of a system for assessing the condition of sanitary sewers. The joint detector showed 100% accuracy in detecting the existence of pipe joints. Similar techniques are used to detect cracks and service laterals in pipe sections. It was shown that by combining the results of the joint detection ANN with those for crack detection, the overall condition of the pipe section can be determined.

There are some limitations to the prototype system. The image data used for training the networks and simulation were reduced by one-quarter of the original image in order to reduce computational time. If the SSET data are fully utilized, more accurate results are expected. In the next stage of the research, the interpretation methodology will be validated in two steps. Initially, it will be validated against inspection reports generated by using CCTV technology. One of the key issues that have to be considered at this stage is resolving the possible differences between inspection reports (using CCTV) for the same sewer line. The writers plan to use a weighting scheme that assigns weights to the inspection reports, based on experience of the inspector.

Once that is completed, the interpretation methodology will be tested using SSET measured data on live sewers. In this case, data are available from three major data acquisition modes—CCTV, optical scanner, and gyroscopic technology. Each of these modes identifies different defects with different levels of accuracy. Hence, the interpretation accuracy (for each mode) will be checked on cracks, joints, corrosion, and roots. Field conditions will have major impacts on the data collection and hence on the validation. The impacts of these conditions cannot be completely identified until the characteristics of the operating environment are better known. The writers are in the process of obtaining the assistance of field personnel involved in the use of both CCTV and SSET for the development of a more comprehensive validation plan.

ACKNOWLEDGMENTS

This research was primarily funded by a grant from the Purdue Research Foundation and in part by grant CMS-9973509 from the National Science Foundation. Their support is gratefully acknowledged. Any opinions, findings, conclusions, or recommendations expressed in this study

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are those of the writers and do not necessarily reflect the views of the National Science Foundation and the Purdue Research Foundation. The writers thank Dr. Tom Iseley, of Blackhawk Pipeline Assessment Services, and Dr. Kenzi Karsaki, of the CORE Corporation, for providing the SSET data used in the validation.

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