AUTOMATED UNDERGROUND PIPE CONDITION ASSESSMENT BY IMAGE ANALYSIS OF THE STATE-OF-THE-ART SEWER SCANNER AND EVALUATION TECHNOLOGY SURVEYS

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ABSTRACT

Closed Circuit Television (CCTV) surveys are used widely in North America to assess the structural integrity of sewage 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 thousands of miles of pipeline images due to fatigue and cost. In addition, manual inspection for surface defects in the pipeline has a number of drawbacks, including subjectivity, varying standards, and consumption of time. These concerns have motivated the Centre for Advancement of Trenchless Technology (CATT) to conduct a research project for the development of an automated underground sewer pipe inspection system, based on the state-of-the-art Sewer Scanner and Evaluation Technology (SSET) survey for major cities in North America.

The paper presents a system for the application of computer vision techniques to the automatic assessment of the structural condition of sewers from SSET scanned images. Automatic recognition of various pipe defects is of considerable interest since it solves problems of fatigue, subjectivity, and ambiguity, leading to economic benefits. The proposed system can provide accuracy, efficiency, and economy of sewer pipe examination. The main efforts of the paper are placed on investigating algorithms and techniques for image processing, pipe joint/lateral discrimination and crack detection. For development of an automated pipe inspection system the issues explored are: various signals and image processing concepts, nonlinear filtering, feature extraction, pattern recognition, and artificial intelligence. In this paper, an attempt has also been made to develop the framework for cost model based on detected defect population. The proposed system could overcome many of the limitations of the current CCTV surveys, and can provide a more accurate assessment of underground sewage pipe conditions.

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 sewer pipeline collection systems represent a major component of this overall investment. Recent studies have shown that, to upgrade or restore municipal infrastructure in Canada to an acceptable level the cost will be in excess of $Can 45 *billion*. Municipal infrastructure systems are eroding due to aging, excessive demand, misuse, mismanagement, and neglect, as shown in Figure 1. Due to its lack of visibility, rehabilitation of underground infrastructure is frequently neglected until a catastrophic failure occurs, resulting in difficult and costly rehabilitation.

While CCTV technology has advanced, the basic process and results have remained unchanged [1]. The technician has to identify pipe defects in a TV monitor located in a control vehicle at the job site. The potential weak link in this process is the judgement that the field technician must exercise when identifying and classifying pipe defects in the field. Many factors, such as experience, mental awareness, equipment capability, field distractions and interruptions, impact the judgment. An

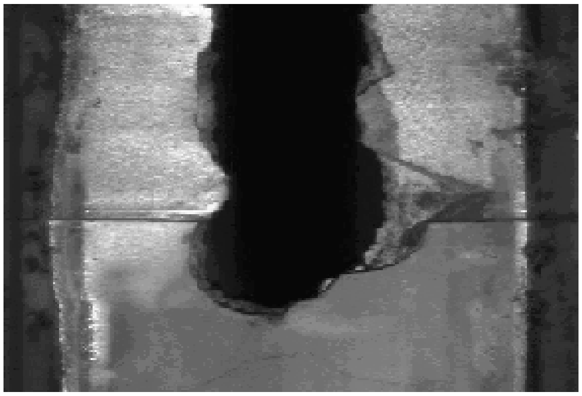

Figure 1: Underground pipe image showing a large hole, scanned by PSET (Core Corp.) in the city of Albuquerque.

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. With recent developments in the hardware and software for computer vision technology, an automated sewer-pipe inspection system is possible and achievable.

In this study, a computer vision system is established for the automatic assessment of the structural condition of underground sewer pipes. The primary objective of this research is to develop an automated underground pipe inspection system, based on the state-of-the-art PSET survey for 10 major cities in North America. The main effort is concentrated on the investigation of image processing algorithms for detection of defects, and artificial intelligence techniques for classification of these defects. An attempt has also been made to set out the framework for cost and deterioration model based on the detected defect population. The paper is organized as follows. Section 2 gives a short review of repair and rehabilitation methods, followed by description of recent development in sewer scanning technology in Section 3. Section 4 presents image processing and segmentation techniques for detection of defects. Section 5 shows some methods for extraction of defect features. Fuzzy neural network classification methodology is described in

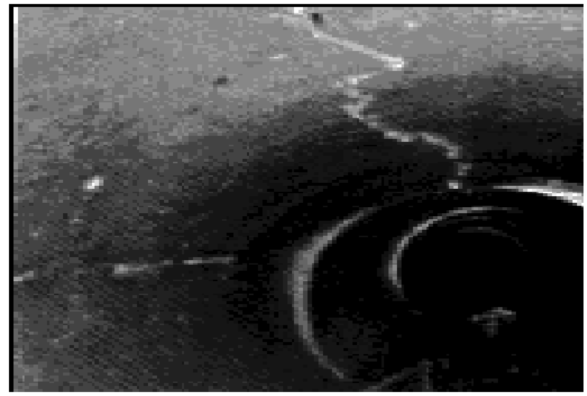

Figure 2: CCTV video image showing joint and longitudinal crack.

Section 6. Section 7 presents the proposed system evaluation and Section 8 gives short description of the proposed cost and deterioration model. Finally, conclusion is given in the end.

2. Sewer Pipes Inspection

Interior defects generally present the first warnings of problems that could occur within sewer lines. 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. The technician attempts to classify each defect (i.e., cracks, holes, root intrusion, misalign joints, defective laterals, etc.) according to the various levels of deterioration and risk. Thus, diagnosis of defects depends on experience, capability, and concentration of the operator, making the detection of defect error prone. The typical CCTV video image is shown in Figure 2.

3. Sewer Scanner and Evaluation Technology Survey (SSET)

Sewer scanner and evaluation technology (SSET) is an innovative technology for obtaining images of the interior of sewer pipe [2]. SSET is developed by TOA Grout, CORE Corp.,

Figure 3: SSET probe for obtaining an unfolded image of sewer pipe surface.

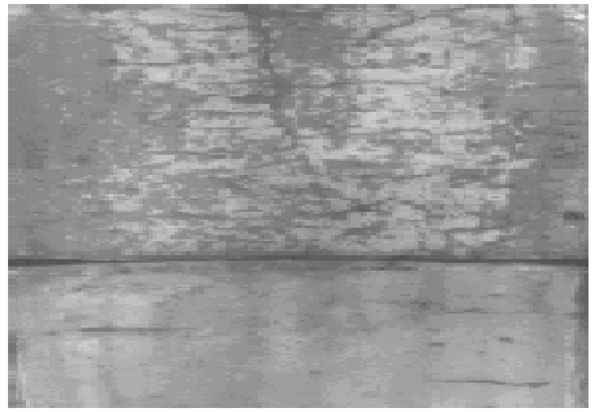

Figure 4: Pipe image showing a joint and multiple cracks, most severely above the joint

California, and the Tokyo Metropolitan Government's Sewer Services (TGS) Company. SSET is a system that offers a new inspection method minimizing some of the shortcomings of the traditional inspection equipment that relies on a CCTV inspection. This is accomplished by utilizing scanning and gyroscopic technology. The SSET probe that obtains an unfolded image of sewer pipe surface is shown in Figure 3. The major benefit of the SSET system over the current CCTV technology is that the engineer will have higher quality image data to make critical rehabilitation decisions. Figure 4 shows the typical image obtained from SSET survey. It can be observed that the pipe joint in this image is a dark narrow straight line across the scanned image, which provide good objects for image processing. In addition to the fact that SSET scanner provides an unfolded image of the sewer pipe, it also has other advantages over CCTV image, like:

1. The image has uniform illumination irrespective of the pipe background.
2. Geometric localization of defects is more precise.
3. Salient features can be easily extracted.
4. Analysis of laterals and joints is easier and precise due to the unfolded quality of image that gives a head-on view of the defects as compared to the oblique view obtained from CCTV.

4. Image Processing and Segmentation

Digital image processing has experienced explosive growth over the past two-decade [3]. The term digital image processing generally refers to processing of a two-dimensional picture by a digital computer. In a broader context, it implies digital processing of any two-dimensional data. Figure 5 shows the fundamental steps in digital image processing and pattern recognition.

After obtaining digital image, the next step deals with preprocessing that image. The key function of preprocessing is to improve the image in ways that increase the chances for success of the other processes. Preprocessing typically deals with techniques for enhancing contrast, removing noise, and isolating regions whose feature indicate a likelihood of alphanumeric information. Image segmentation is the most important stage in any image processing operation. It partitions an input image into its constituent parts or objects. The output of the segmentation stage is usually raw pixel data, constituting either the boundary of a region or all the points in the region itself. In either case, converting the data to a form suitable for computer processing is necessary.

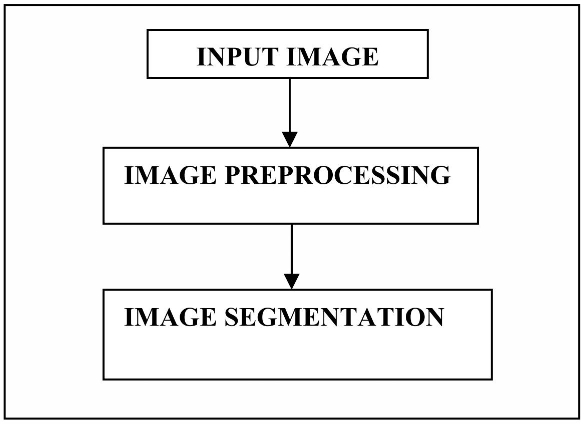

Figure 5: Fundamental steps in digital image processing and pattern recognition.

Figure 6: Enhanced underground pipe image by interpolated multiplier method.

4.1 Color Image Processing and Enhancement

An obstacle to automatic detection and classification of underground pipe defects is that pipe images are usually obtained under different pipe conditions and non-uniform distributed lighting. To effectively recognize defect patterns on the pipe's inner surface, it is necessary to first convert all source images to gray scale and to a standardized background lighting condition.

Many image-processing problems require transformation of color images into gray scale images. After analysis of underground sewer pipe images, it has been observed that taking the average of three primary color bands (red, blue, and green) and converting them into gray scale is not effective for the detection of cracks in sewer pipe. Signal to noise ratio in the various color bands seems to be an obvious function of underground pipe background color. In such a case the task is to develop a model to obtain gray scale by linear weighting of color bands. In this study, the gray scale images are obtained by using Fisher's linear discriminant analysis [4].

To extract the defect information with fidelity from the original image, it is necessary to convert the gray scale image to a standardized background lighting condition. The intensity matrix from an image with a pipe distress contains three types of variations: (1) non-uniform background illumination, a very low-frequency and fairly high-amplitude signal; (2) pipe distress or non-distress irregularities (stains or dark materials on surface), a high-amplitude and strictly negative signal having high-frequency components on the edges; (3) noise caused by heterogeneous materials and granularity, a random, high frequency, and a low-to-medium amplitude signal. The pixel intensity of image $I(p)$, $p=\{x,y\}$ may have the following composition:

$$I(p)=Ib(p)+In(p)+Id(p)$$

where $Ib(p)$ is the background illumination signal; $Id(p)$ is pipe distress signal; and $In(p)$ represents the noise. The algorithm that removes the background illumination considers the frame divided into rectangular windows and starts the process by calculating the average light intensity for all pixels in each of the windows. Once this matrix is purged of every distress intrusion, it is converted into a matrix of multipliers capable of pushing all intensity values to a common base intensity B. This operation will have the effect of converting the variable background intensity $Ib(p)$ to the constant B. Each window multiplier $M(p)$ is calculated according to:

$$M(p) = B/I(p)$$

The result from the enhancement of the original image by the interpolated multiplier method is shown in Figure 6.

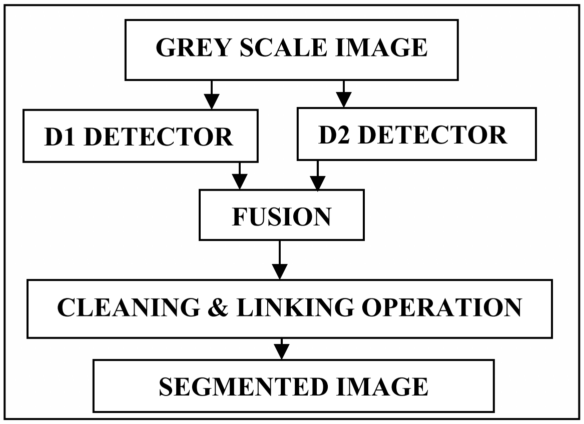

Figure 7: Diagram showing the different steps for detection of linear structures.

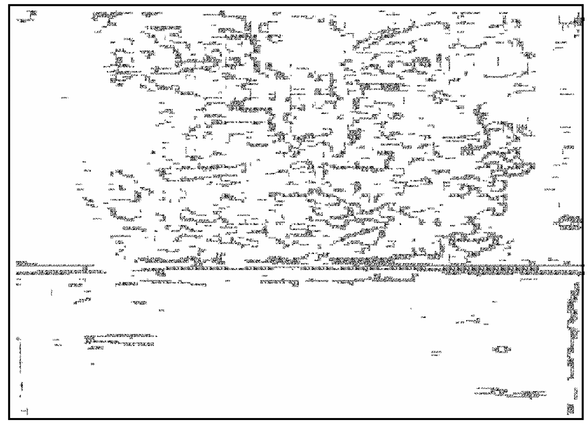

Figure 8: Thresholded responses of the line detectors for multiple cracks in the underground pipe.

4.2 Detection of Linear Structures

In the past 20 years, many approaches have been developed to deal with the detection of linear features on optic or radar images [5-6]. Most of them combine two criteria: a local criterion evaluating the intensity 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 criteria, most of the techniques used for road detection in visible range images are based either on conventional edge or line detectors [7]. They fail in processing all kinds of images because they often rely on the assumption that the noise is white additive and Gaussian, this is not verified in scanned image. These methods, therefore, roughly speaking, evaluate difference of averages, implying noisy results and variable false-alarm rate. The Bayesian framework, which is well adapted for taking some contextual knowledge into account, has been widely used [8]. Edge detection and line finding techniques, of course, have been studied since the early days of this field and are described in textbooks [9,10,11]. However, in spite of the large amount of previous research in this area, and a number of comparative studies [12-13], the choice of algorithms suitable for detection of defects in the underground pipe images is not clear.

To develop suitable algorithm for detection of cracks in underground sewer pipes it is important to define their statistical properties. In the present study, cracks have been defined to have the following characteristics:

- They are usually not in a straight line
- Their width lies within a particular range
- Cracks usually are seen to lie below certain grey-level intensity.

The approach taken in this study for detection of linear structures is based on the fusion of the results from two line detectors, both taking the statistical properties of image into account. Line detector D1 is based on the ratio edge detector [14], widely used in coherent imagery. An in-depth statistical study of its behavior is given in Lopes et. al. [15]. The brightness of pixel *s* is A_s, so the empirical mean μ_i of a given region *i* having n_i pixels is: $\mu_i = \left(\frac{1}{n_i}\right)\sum_{s \in i} A_s$. The response of the edge detector between region i and j is defined as r_{ij}:

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

Detector D2 uses the normalized centered correlation between two populations of pixel [16]. The cross-correlation coefficients ρ_{ij} can be shown to be:

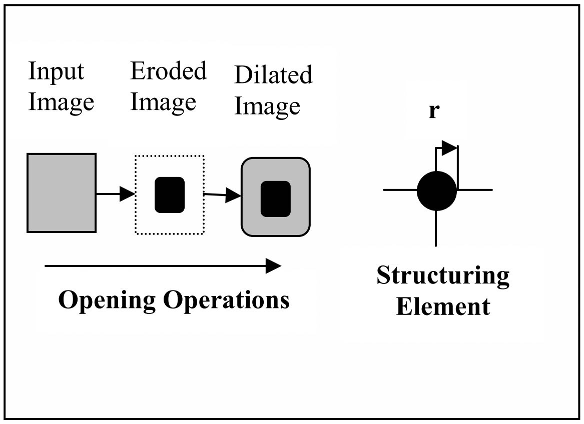

Figure 9: An opening morphological operation with circular structuring element.


Figure 10: Pipe image showing a joint, two laterals, and minor defects.

$$\rho_{ij}^{2} = \frac{1}{1 + (n_i + n_j) * \dfrac{n_i \gamma_i^2 c_{ij} + n_j \gamma_j^2}{n_i n_j (c_{ij} - 1)^2}}$$

where n_i is the pixel number in region i, $c_{ij} = \mu_i / \mu_j$ is the empirical contrast between region i and j, and γ_i is the variation coefficient. Both responses from D1 and D2 are merged to obtain a unique response as well as associated direction in each pixel. The detection results are post-processed to provide candidate segments. Figure 7 shows the diagram for different steps of the proposed method. Threshold response of the line detectors after fusing and linking operations is shown in Figure 8. The crack features detected in the image will be later used for feature extraction and classification.

4.3 Morphological Image Processing

Mathematical morphology provides an approach to the processing of digital images that is based on shape. Appropriately used, mathematical morphological operations tend to simplify image data preserving their essential shape characteristics and eliminating irrelevancies. Morphological operations are derived from the branch of mathematical analysis called Minkowski algebra [17]. Morphological image processing is useful for shape analysis, feature extraction and nonlinear filtering.

Basically, morphological image processing is the analysis of the geometrical relationship between the image and a smaller image called a structuring element.

Here, some background knowledge of mathematical morphology is provided. First, some basic binary mathematical morphological operations are described, as in reference [18]. Let *X* be the set of a binary image and *B* is the set of a structure element (or template), which is also a subset of the universal space *E*. Then:

Binary Erosion

$$X \Theta B = \{ x | x + b \in X \forall b \in B \}$$

Binary Dilation

$$X \oplus B = \{ x + b : x \in X, b \in B \}$$

Binary Opening

$$X \circ B = (X \Theta B) \oplus B$$

Binary Closing

$$X \bullet B = (X \oplus B) \Theta B$$

From the above it is observed that erosion has the effect of shrinking the image *X*, while dilation expands it. Opening removes narrow isthmuses, capes and islands, while closing fills gulfs, and small holes. An opening with a circular structuring element of radius *r* is performed (Figure 9) by removing a strip of object with the width

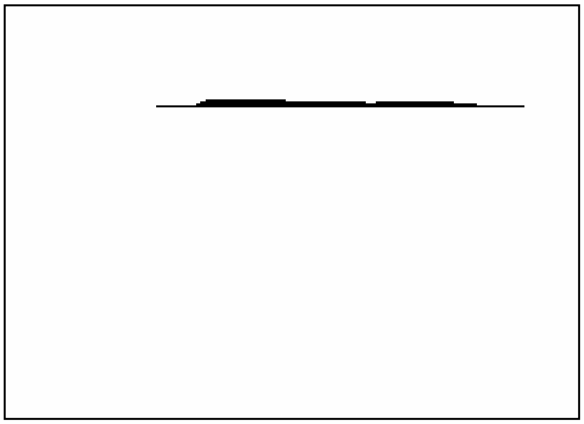

Figure 11: Analysis of joint by mathematical morphology.

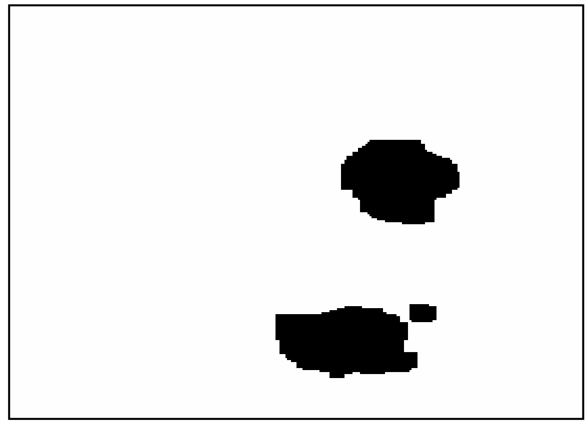

Figure 12: Analysis of lateral by mathematical morphology.

r along the object boundary (erosion) and then adding a strip of object with the same width back on to whatever portion remains of the object (dilation). Small features will be removed and can not be recovered, whereas large features will shrink and then expand to their original size. With different sizes of structuring elements, performing a series of opening operations can then identify features of various sizes. Mathematically speaking, the size measurement at a point of object area is equal to the radius of the largest inscribed disk that contains the point and lies entirely within the object area. A unique feature of the generalized size analysis is that it does not require a predefined 'single object', therefore, it is especially suitable for characterizing an irregular and interconnected region.

In the present work, grey scale morphology is applied to an image (Figure 10) for analysis of joints and laterals. The main objective of this approach is to segment out the background and other objects from the image and hence the joints and laterals can be easily obtained by a subsequent global thresholding technique. Since the joint is straight and horizontal in the scanned images, the horizontal structuring element is used for analysis. For extraction of lateral the square shaped structuring element is used. Figure 11 shows the capability of opening operators for analysis of joint, and Figure 12 shows the extraction of laterals. To define defective joints and laterals the information obtained from these images will be used.

5. Image Feature Extraction

In a system designed to distinguish objects of different types, it is important to decide which characteristics of the objects should be measured to produce descriptive parameters. Proper selection of the features is important, since only these will be used to identify the objects. Figure 13 shows the fundamental steps in image feature extraction and classification.

Many features can be used to describe an object. The most basic of all image features is the measures of image amplitude in terms of spectral value, luminance, tristimulus value, or other units. The most common object measurements made are those that describe shape. Image transforms provide the frequency domain information on the data. Transform coefficient feature extraction has proved practical in several applications in which the transform domain features are used as inputs to a pattern classification system [19]. The textural features of an object can often be used to discriminate between the surface finish of a smooth or coarsely textured object [20]. The gray level histogram of an image often contains sufficient information to allow

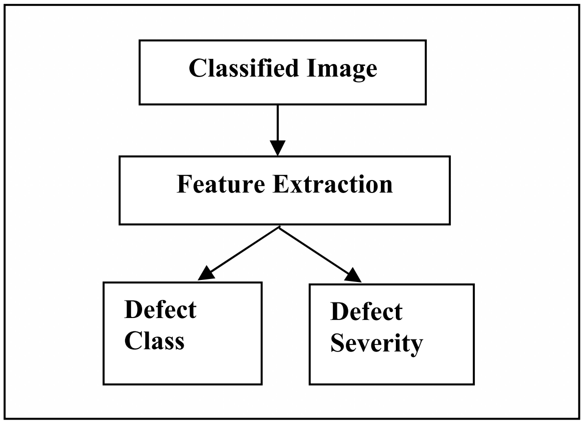

Figure 13: Fundamental steps in image feature extraction and classification.

analysis of the image content and, in particular, to discriminate between objects. The second-order histogram features are based on the definition of the joint probability distribution of pairs of pixel [21]. Various measures have been suggested [22] to specify the energy spread about the diagonal of joint distribution.

Ideally, the features will be able to clearly distinguish between classes of defects. Since this is rarely the case, and since some feature will be more important than others, a minimal set of features that adequately distinguish between the classes must be found. Reducing the number of features will also be computationally advantageous. In this study, a set of 25 features is extracted that describe the geometric attributes of the cracks in the underground pipe images. Various features like mean, standard deviation, second order moment, co-occurrence matrix, and morphological features are calculated. From this large set of features five optimal features based on gray level concurrence matrix have been kept for classification.

The features extracted will be used for classification by the fuzzy neural network. The features will be classified according to the nature and severity of the underground sewer pipe defect.

6. Fuzzy Neural Network Classifier

Underground pipe defects appear in the form of random shaped cracks. These defects have been classified, but the decision to put a defect in a particular class can vary from person to person or from time to time. For such a complicated decision rule problem, the solution is based on the use of a neural network that can mimic human reasoning. The benefits of the neural network is the generalization ability about the untrained samples due to the massively parallel interconnections and the ease of implementation simply by training with samples for any complicated rule or mapping problem. The utility of fuzzy sets [23] lies in their ability to model the uncertain or ambiguous data so often encountered in real life. Therefore, to enable a system to take care of real life situations in a manner more like humans, the concept of fuzzy sets into the neural network has been incorporated.

6.1 Backpropagation Neural Network

An artificial neural network (ANN) attempts to mimic, in a very simplified way, the human mental neural structure and functions [24]. It can be characterized as a massively parallel interconnection of simple neurons that function as a collective system. The ability of a neural network to process information is obtained through a learning process, which is the adaptation of link weights so that the network can produce an appropriate output. In general, the learning process of an ANN will reward a correct response of the system to input by increasing the strength of the current matrix of nodal weights. Therefore, the likelihood of producing similar output when the same inputs are entered in the near future will increase. The learning process may be supervised or unsupervised based on the availability of target output. In supervised learning, inputs proceed through the network and produce an output. The difference between this output and the target output represents an error that is then propagated back through the network to 'train' it. In unsupervised learning, the network automatically detects important features and organizes the input data into classes based on these features.

For supervised pattern recognition, the most commonly used ANN is the feed-forward network trained using the back-propagation algorithm [25] that is adopted in the present study. The backpropagation algorithm can be described in three equations. First, weight connections are changed in each learning step (*k*) with

$$\Delta w_{ij(k)}^{[s]} = \eta(t)\delta_{pj}^{[s]} x_j^{[s-1]} + m\Delta w_{ij(k-1)}^{[s]}$$

Second, for output nodes it holds that

$$\delta_{pj}^{[o]} = (d_j - o_j) f_j^{'}(I_j^{[s]}$$

and third, for the remaining nodes it holds that

$$\delta_{pj}^{[s]} = f_j^{'}(I_j^{[s]}) \sum_k \delta_{pk}^{[s+1]} w_{jk}^{[s+1]}$$

where $x_j^{[s]}$ = actual output of node *j* in layer *s*; $w_{ij}^{[s]}$ = weight of the connection between node *I* at layer (*s-1*) and node *j* at layer (*s*); $\delta_{pj}^{[s]}$ =measure for the actual error of node *j*; $I_j^{[s]}$ = weighted sum of the inputs of node *j* in layer *s*; $\eta(t)$ = time-dependent learning rate; *f*( ) = transfer function; m = momentum factor (between 0 and 1); and d_j, o_j = desired and actual activity of node *j* (for output nodes only).

6.2 Neuro-Fuzzy Algorithm

Human reasoning is somewhat fuzzy in nature. The combination of neural networks and fuzzy logic into neuro-fuzzy system can help to enhance the performance of the system by using special learning algorithms.

In general, there are two kinds of combinations between neural networks and fuzzy systems. In the first approach neural network and fuzzy system work independently of each other. The combination lies in the determination of certain parameters of a fuzzy system by a neural network, or a neural network learning algorithm. This can be done offline, or online during the use of the fuzzy system. The second kind of combination defines a homogenous architecture, usually similar to the structure of a neural network. This can be done by interpreting a fuzzy system as a special kind of neural network, or by implementing a fuzzy system using neural network. Besides these models there are approaches in which a neural network is used as a preprocessor or as a postprocessor to a fuzzy system. Such combinations do not optimize a fuzzy system, but only aim to improve the performance of the combined system. Learning takes place in the neural network only; the fuzzy remains unchanged [26]. In this case the improvement of neural network learning is the main intention.

To increase the classification rate, a neuro-fuzzy algorithm is employed that combines neural networks and the fuzzy concepts. Neural networks have learning capability and the fuzzy concepts can absorb variability in feature values. In this study, fuzzy concept is applied simply in converting feature values into fuzzified data, which are inputs to the backpropagation neural network algorithm. Sometimes, variation of feature values is large, then it is difficult to classify features correctly based on these feature values. To solve this problem, each defect feature value is converted into three fuzzy data, then learning is performed with these fuzzified data using the backpropagation algorithm. Finally, defects are classified using the backpropagation algorithm.

To convert five normalized features into 15 fuzzy data, the *MAX* and *MIN* values are

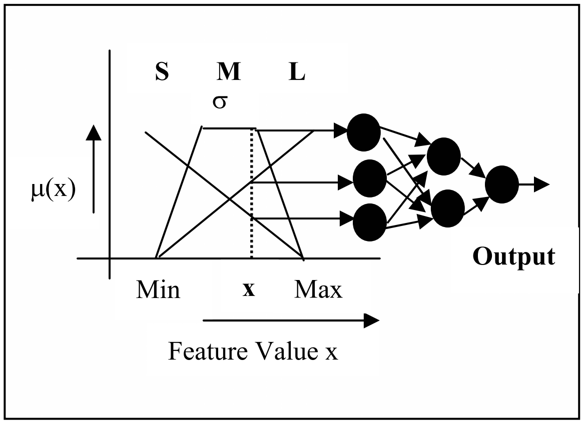

Figure 14: Neuro-Fuzzy network with trapezoidal membership function.

Pipe Defect Recognition Method	Pipe Defect Recognition Rate (%)
Backpropagation Algorithm -	**88.51**
Neuro-Fuzzy Algorithm	
Triangular Membership Function -	**91.74**
Trapezoidal Membership Function -	**93.26**

Table 1. Classification rates by conventional backpropagation and neurofuzzy algorithm.

determined that are the maximum and minimum feature values for entire data set, respectively. As shown in Figure 14 three membership functions are generated denoted by '*S*' (small), '*M*' (medium), and '*L*' (large). Note that these membership functions are specified by *Min* and *Max*, as shown in Figure 14. Then three fuzzy data is computed for each feature values and uses these data as the input data to neural networks. In Figure 14 $\mu_S(x_i)$, $\mu_M(x_i)$, and $\mu_L(x_i)$ are three fuzzy data of an input feature value (x_i), corresponding to linguistic variables of '*S*', '*M*', and '*L*', respectively. The trapezoidal membership function, as shown in Figure 14, locates at the average value of features of the same image, and has a maximum value of 1 over the limited range that is specified by the standard deviation of the feature value. To generate a linguistic variable the average and standard deviation of the feature values are computed. Then the interval between *MIN* and *MAX* is uniformly divided into several subintervals, where *MIN* and *MAX* represents the minimum and maximum of average values of the specific feature, respectively. The membership function of each image is centered at the average value of the features of the image. Variation of feature values for the same image is allowed by employing the trapezoidal membership function, i.e. the width at the top of the trapezoidal membership function is set to σ_i, where σ_i denotes the standard deviation of the *i*th feature value. Note that for input data greater (smaller) than *MAX* (*MIN*) we clip the membership value to 1 (0).

6.3 Experimental Verification

To test the proposed approach 256x256 pixels color images of sewer pipes are used. Fifty samples are used for training and twenty samples for testing. All values used for training and testing are the normalized values. For performance comparison with the proposed neuro-fuzzy algorithm, the conventional backpropagation algorithm is simulated.

In the backpropoagation algorithm to reduce the computational complexity and to avoid local minima problem, the learning rate and momentum factor are varied adaptively. In the input layer, there exist five nodes for five features, and one neuron in the output layer for defect classification. The number of nodes in the hidden layer is determined experimentally: in this simulation the number is selected which gives the best classification results, i.e. five neurons are used. In the neuro-fuzzy algorithm 15 fuzzy data are used in the input layer and in the hidden and output layer the same number of neurons are used as in the conventional backpropagation algorithm. Table 1 shows the classification results by the backpropagation algorithm and proposed neuro-fuzzy algorithm using a triangular and trapezoidal membership functions.

7. Proposed System Evaluation and Calibration

The aim of present study is to develop an automated underground pipe inspection system that can be synthesised with a rational decision making model. The system will be designed to decrease the workload of the operator, at the same time increasing efficiency and allowing the operator to concentrate on defective areas, rather than spending time in looking at monotonous clean images.

The system will be evaluated by analyzing the images obtained from PSET survey in the city of Toronto. Evaluation will be based upon the probability of false detection, misclassification, and insensitivity of the system in comparison to the human operator. False detection is defined as the percentage of times the system classifies non-defect as defect. Misclassification is defined as the percentage of classifying one defect as another. Insensitivity is defined as the percentage of times the system classifies a defect as a non-defect.

The resulting probabilities will be interpreted to obtain an achievable trade-off value of high detection probability and low false-alarm detection. This evaluation will be used to tune the system for development of computationally efficient and robust automated underground pipe inspection system as shown in Figure 15.

8. Proposed Sewer System Deterioration and Cost Model

In general sewers have a design life of about 50 to 60 years, but some fail earlier due to structural defects, wear and tear, hydraulic overloading, and deterioration. Determining the condition of a sewer pipe,

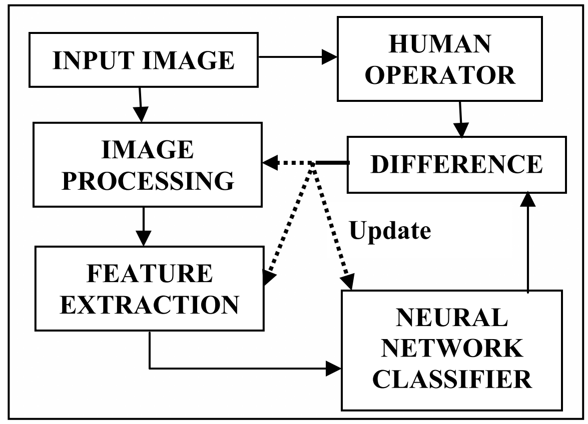

Figure 15: Proposed automated system evaluation and calibration

using automated inspection technique, before it collapses can be helpful in avoiding these failures. Once the condition of the pipe is known, rehabilitation can be scheduled to correct initial defects.

Rehabilitation analysis of a pipe section includes identifying defects, evaluating the severity of the defect and selecting rehabilitation alternatives to counter sewers. Sewer system deterioration and cost model (SSDCM) combine condition assessments, predictions of future conditions, rehabilitation methods, if needed, that could extend the sewer life. They are designed to provide information and data useful for analysis so that public work managers and engineers can make consistent and cost-effective decisions related to the preservation of these sewer systems.

Once a pipe section has been inspected by SSET camera and evaluated by the proposed automated system, then SSDCM can be used to develop performance prediction models, prioritize the rehabilitation or maintenance needs. A detailed survey questionnaire has been sent to the municipalities and sewer contractors in Canada and United States. From the data collected it is proposed to develop a SSDC model based on Markov chain process [27]. The Markov chain, a probability-based method, will be used in the model to reflect the stochastic nature of the underground sewer pipe conditions. This model will then be used to predict the deterioration rate and cost based on the current condition of the pipe, cost of repair, repair method, and the aggregate opinion of the experts in this field.

9. Conclusion

A practical use of computer vision for automatic assessment of the structural condition of sewers from SSET scanned images has been suggested and implemented. Two main obstacles are the poor background illumination, and the highly patterned surface of sewer pipes, which causes problem for detection of defects. The defect detection techniques used in this study, especially the generalized edge detection, are robust for detection of cracks, but for root extraction, the techniques need to be improved further. For joint and lateral analysis, a technique based on mathematical morphology has been proposed and investigated. The technique is quite effective if the original size of the joint and lateral is available or estimated accurately.

A fully automated sewer pipe inspection system is envisaged, in which successive image frames are analyzed until a pipe defect is identified. The defective frame would be selected, and analyzed using the techniques discussed in this study. Such a scheme would extract valuable information from SSET surveys. This goal has not yet been achieved, and although there is still a lot of work to be done, the principles have been developed and demonstrated in this paper. The proposed automated system has the potential to overcome the limitations of the current CCTV inspection, and can provide a more accurate assessment of underground sewer pipe conditions.

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