Proceedings of the 1999 IEEE
International Symposium on Intelligent Control/Intelligent Systems and Semiotics
Cambridge, MA • September 15-17, 1999

Underground Pipe Cracks Classification Using Image Analysis and Neuro-Fuzzy Algorithm

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Abstract

Pipeline surface defects such as cracks cause major problems for asset managers, particularly when the pipe is buried under the ground. The manual inspection of surface defects in the underground pipes has a number of drawbacks, including subjectivity, varying standards, and high costs. Automatic inspection system using image processing and artificial intelligence techniques can overcome many of these disadvantages and offer asset managers an opportunity to significantly improve quality and reduce costs. A recognition and classification of pipe cracks using image analysis and neuro-fuzzy algorithm is proposed. In the pre-processing step, the cracks in the pipe are extracted from the homogenous background. Then, based on a prior knowledge of cracks, five normalised features are extracted. In the classification step, a neuro-fuzzy algorithm is proposed that employs a trapezoidal fuzzy membership function and modified error backpropagation (EBP) algorithm.

1. Introduction

Municipal infrastructure systems are eroding due to aging, excessive demand, misuse, mismanagement, and neglect, as shown in Figure 1. Closed Circuit Television (CCTV) surveys of underground pipes are used widely in North America to assess the structural integrity of pipes [1]. CCTV surveys are conducted using a remotely controlled vehicle carrying a television camera through an underground pipe. The data acquired from this process consist of a videostream, photographs of specific defects, and records produced by technician. The diagnosis of defects depends largely on the experience, capability, and concentration of the operator, making the detection of defect error prone. An automated underground pipe inspection system is required, which can extract and assess the structural condition of pipes to ensure accuracy, efficiency, and economy of underground pipe examination.

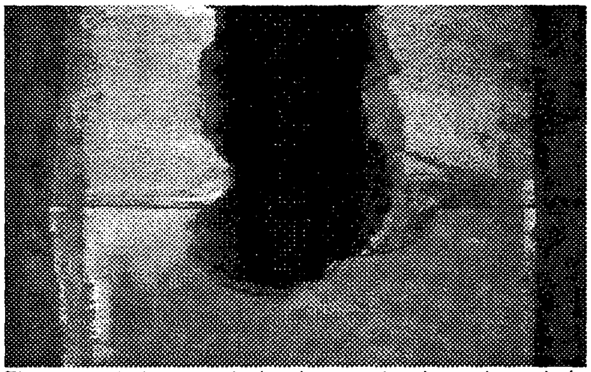

Figure 1: Underground pipe image showing a large hole, scanned by PSET (Core Corp.) in the city of Albuquerque.

In this paper, a defect detection methodology based on the local detection of linear structures and a neuro-fuzzy algorithm is proposed. The main effort is concentrated on the investigation of image processing algorithms for detection of cracks, and artificial intelligence technique for classification of severity of these cracks. The scanned images for this study are obtained by Pipe Scanner and Evaluation Technology (PSET) surveys for major cities in North America.

2. PSET Surveys

Pipe scanner and evaluation technology (SSET) is an innovative technology for obtaining images of the interior of pipe [2]. PSET is developed by TOA Grout, CORE Corp., California, and the Tokyo Metropolitan Government's Services (TGS) Company. PSET 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. Typical scanned images of underground pipe with various defects are shown in Figures 2(a) and 2(b). The major benefit of the PSET system over the current CCTV technology is that the engineer will have higher quality image data to make critical rehabilitation

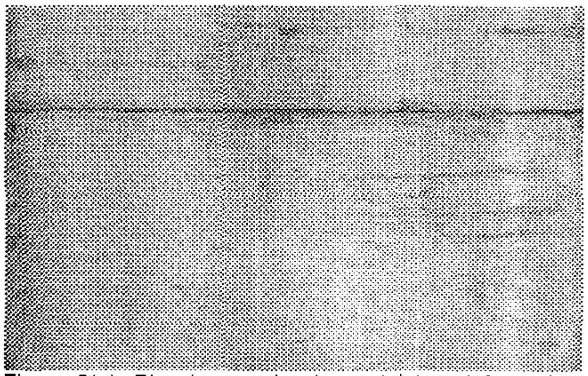

Figure 2(a). Pipe image showing a joint and few minor cracks.

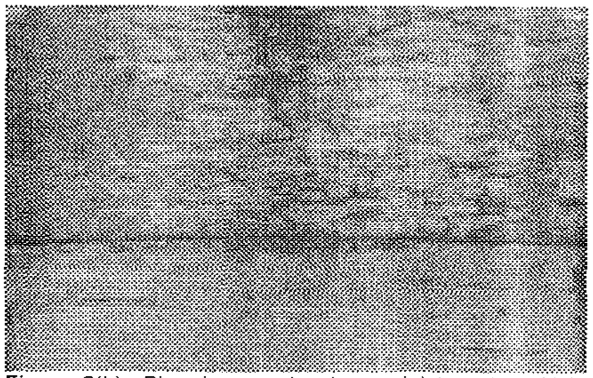

Figure 2(b). Pipe image showing a joint and multiple cracks, most severely above the joint.

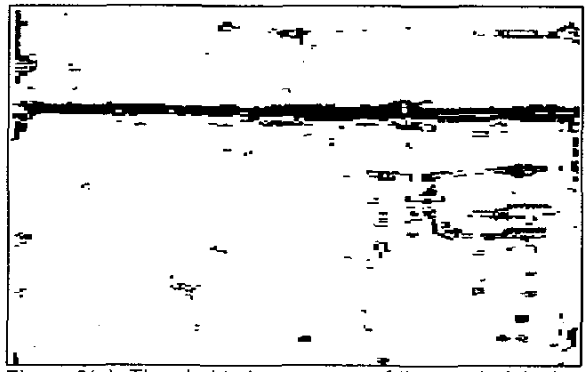

Figure 3(a). Thresholded responses of the crack detectors for minor cracks in the underground pipe.

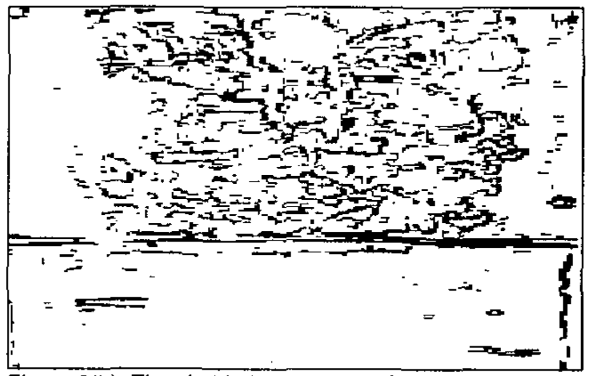

Figure 3(b). Thresholded responses of the crack detectors for multiple cracks in the underground pipe.

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

3. Image Analysis

In the computer vision literature one can find various techniques addressing different types of data, including natural and artificial textures, synthetic aperture radar images, and magnetic resonance images [3,4,5,6]. In analysing underground pipe scanned image data, one needs to consider complications due to the inherent noise in the scanning process, irregularly shaped objects (roots, cracks, and holes) as well as the wide range of pipe background patterns. One of the major problems is to detect cracks that are camouflaged in the background of corroded areas, debris, patches of repair work, areas of poor lighted conditions.

In the past 20 years, many approaches have been developed to deal with the detection of linear features on optic [7,8] or radar images [9,10]. Most of them combine two criteria: a local criterion evaluating the radiometry on some small neighborhood surrounding a target pixel to discriminate lines from background and a global criterion introducing some large-scale knowledge about the structures to be detected. Concerning the local criteria, most of the techniques used for pavement distress detection in scanned images are based either on conventional edge or line detectors [11,12]. These methods evaluate differences of averages, implying noisy results and variable false-alarm rates [13].

The approach taken in this study for detection of cracks falls within the scope of the Bayesian framework. It is based on the fusion of the results from two detectors D1 and D2, both taking the statistical properties of image into account. Crack detector D1 is based on the ratio edge detector [14], widely used in coherent imagery. Detector D2 uses the normalised centered correlation between two populations of pixel [15]. The detection results are post-processed to provide candidate segments. Threshold responses of the crack detectors after fusing and linking operations are shown in Figures 3(a) and 3(b).

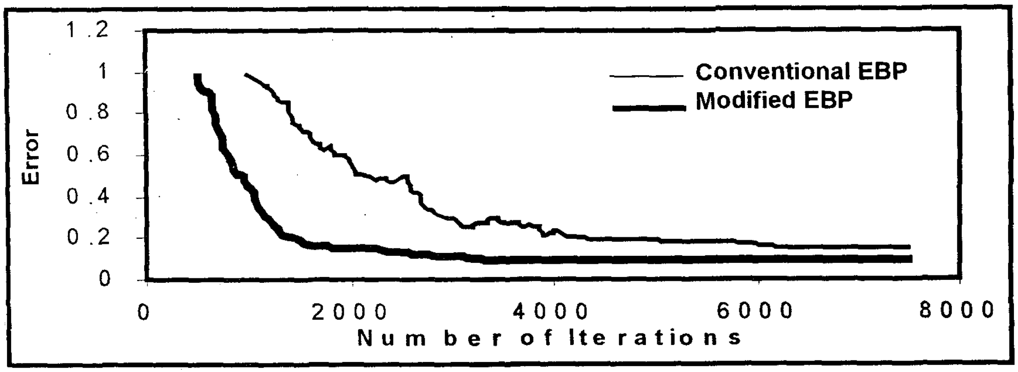

Figure 4. Convergence characteristics of the error backpropagation algorithm.

4. Feature Extraction

Selection of an appropriate set of features is one of the most important tasks for any defect classification system. The primary goal of feature extraction is to obtain features that maximise the similarity of objects in the same class while at the same time maximising the dimensionality reduction of data, computational efficiency and reduction of memory requirements of the classifier. This is particularly important when neural networks are used to perform the classification tasks as the dimensionality reduction of the input not only removes the redundancy of the data but also enables the use of a smaller size network structure which can be trained easier and has improved generalisation capability.

The salient features of the data can be extracted through a mapping, such as Fourier transform, discrete cosine transform, Karhunen-Loeve (KL) transform, or principal component (PC) method, from a higher dimensional input space to a lower dimensional representation space. The efficiency of a chosen mapping approach is judged based on the degree of data compaction subject to the constraint that the original data can be reconstructed with minimal distortion. Based on this criterion, the following features or attributes that characterize each object are extracted after appropriate transformations:

- Hough transform features,
- Morphological analysis features,
- Amplitude and shape statistics,
- Regression analysis features, and
- eigenvector analysis features

After extracting over 25 features, thorough optimisation and ranking are performed to reduce the classification dimension down to 5, depending on the stage in hierarchical classification [16].

5. Defect Classification

Underground pipe defects appear in the form of randomly shaped cracks. The decision making of the pipe condition by human experts is based on very complicated rules such as "if the total area of crack is *A*, then it gives a penalty *f* to the decision, if the total area of crack is ***B***, then it gives a penalty ***g*** to the decision, if a pipe has ***f***, ***g***,..., ***k*** penalties then the final decision of the pipe is $\mathbf{P}^{th}$ class." To set all these complicated rules, many efforts and time consuming discussions would be required by human experts. In practice, carrying out this task would be even harder if different criteria existing among the experts about the defects were taken into account. Therefore, there has been a lack of normalization in assessment of underground pipe condition.

For such a complicated decision rule problem, the solution is based on the use of a neural network paradigm that can mimic the human reasoning [17]. The benefits of the neural network is the generalization ability [18] about the untrained samples due to the massively parallel interconnections and easiness of implementation for any complicated rule or mapping problem.

5.1. Classification using EBP algorithm

In this section crack classification using an EBP algorithm [19] is discussed. Conventional EBP algorithm used a fixed learning rate and momentum factor, thus to reduce the learning time and to avoid local minima these parameters must be determined adaptively. A variable learning rate and momentum factor is used by iteratively updating weights, resulting in the modified EBP algorithm. In the modified EBP algorithm, the learning rate η, momentum factor α, and weight ω are updated by the following equations, respectively:

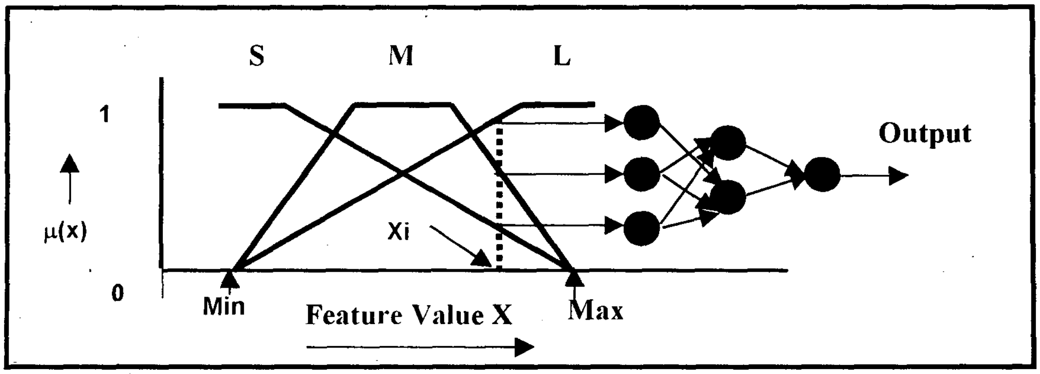

Figure 5. Neuro-Fuzzy network with trapezoidal membership function.

$$\Delta\eta_{jk}(m+1)=\varepsilon\left(\frac{\partial E_p}{\partial\omega_{jk}}\right)^2+\beta\Delta\eta_{jk}(m),$$

$$\Delta\alpha_{jk}(m+1)=\mu\left(\frac{\partial E_p}{\partial\omega_{jk}}\right)^2+\gamma\Delta\alpha_{jk}(m),$$

$$\Delta\omega_{jk}(m+1)=-\eta_{jk}\frac{\partial E_p}{\partial\omega_{jk}}+\alpha_{jk}\Delta\omega_{jk}(m)$$

where ε, β, μ, and γ denote constants and m represents the iteration step. Subscripts j and k signify the jth neuron of the input (hidden) layer and kth neuron of the hidden (output) layer, respectively. E_p represents the total error function at the pth layer. In Figure 4, the convergence characteristics of the conventional and modified EBP algorithms are shown. The network is constructed by five input neurons, seven neurons in the hidden layer, and three output neurons for three classes of crack defects. Parameter values are selected experimentally: in the conventional algorithm, the learning rate and momentum factor are set to 0.7 and 0.15, respectively, whereas in the modified algorithm, 0.5 and 0.2, respectively. Figure 4 shows that the modified EBP algorithm converges much faster than the conventional one.

5.2. Classification using Neuro-fuzzy algorithm

To increase the recognition 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. The fuzzy concept can be combined with neural networks in various ways. In this study the fuzzy concept is applied simply in converting feature values into fuzzified data, which are inputs to the modified backpropagation neural network algorithm. In the proposed neuro-fuzzy algorithm the fuzzy data is used as inputs to neural networks. Sometimes, variation of feature values is large, and then it is difficult to classify defects correctly based on these feature values. To solve this problem, each defect feature value is first converted into three fuzzy data [20], then learning is performed with these $3I$ fuzzy data using the modified EBP algorithm. Finally, defects are classified using the modified backpropagation algorithm.

To convert five normalised features into 15 fuzzy data, the *MAX* and *MIN* values are determined that are the maximum and minimum feature values for entire data set, respectively. As shown in Figure 5, three membership functions denoted by '*S*' (small), '*M*' (medium), and '*L*' (large) are generated. Note that these membership functions are specified by *MIN* and *MAX*, as shown in Figure 5. Then three fuzzy data is computed for each feature values and uses these data as the input data to neural networks. In Figure 5 $\mu_S(x_i)$, $\mu_M(x_i)$, 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 5, locates at the average value of features of the same defect, 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 of the defect is 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 defect. 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

CLASSIFICATION METHOD	CLASSIFICATION RATE (%)
Euclidean Distance Method	81.1
Error Backpropagation Algorithm	88.2
Fuzzy Algorithm	
Triangular Membership Function	83.2
Trapezoidal Membership Function	85.7
Neuro-Fuzzy	
Triangular Membership Function	91.7
Trapezoidal Membership	93.2

Table 1. Classification rate by various methods

standard deviation of the *i*th feature value. Note that for input data greater (smaller) than *MAX* (*MIN*) the membership value is clipped to 1 (0). These membership functions for 50 images are stored in a database for neural network learning.

6. Experimental Results

Underground pipe colour images of 256x256 pixels are used to test the proposed approach. Fifty samples are used for training and twenty-five samples for testing. For each crack type twenty-five 256x256 images are obtained with different illumination and background conditions, each image uniformly quantized to eight bits. All the feature values used for training and testing are the normalised values.

For performance comparison with the proposed neuro-fuzzy algorithm, conventional algorithms such as Euclidean distance method, EBP algorithm, and fuzzy methods with triangular and trapezoidal membership functions are simulated.

In the modified EBP 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, but three neurons in output layer for three class of pipe defect. The number of nodes in the hidden layer is determined experimentally. In the proposed neuro-fuzzy algorithm fifteen fuzzy data is used in the input layer and in the hidden and output layer the same number of neurons are used as in the modified EBP algorithm. Table 1 shows the classification results by the proposed neuro-fuzzy algorithm and other conventional algorithms. From Table 1 it can be observed that the proposed neuro-fuzzy algorithm using a trapezoidal membership function yields better classification results than the Euclidean distance method, EBP algorithm, and fuzzy-based algorithms.

7. Conclusion

In this study, an underground pipe defect classification using a neuro-fuzzy algorithm is proposed that combine the conventional backpropagation algorithm and the fuzzy concepts. In the pre-processing step, the cracks are detected from the background of the pipe surface, and then five crack features are extracted. These features are fuzzified and applied to the modified backpropagation algorithm in the classification step. Simulation results show that the proposed neuro-fuzzy algorithm using a trapezoidal membership function gives better classification results than the conventional algorithms. Further research will focus on development of efficient learning and classification algorithms for a large set of underground pipe images.

Acknowledgement

This research is supported by Natural Science and Engineering Research Council (NSERC) of Canada, and Liqui-force Services Ltd., Ontario, Canada. The authors would also like to thank CORE Corp., California, for providing the scanned images of underground pipe needed for this research, and the municipalities in North America for their valuable inputs.

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