Classification of Underground Pipe Scanned Images Using Feature Extraction and Neuro-Fuzzy Algorithm

Sunil K. Sinha and Fakhri Karray

***Abstract*—Pipeline surface defects such as holes and cracks cause major problems for utility managers, particularly when the pipeline is buried under the ground. Manual inspection for surface defects in the pipeline 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 utility managers an opportunity to significantly improve quality and reduce costs. A recognition and classification of pipe cracks using images analysis and neuro-fuzzy algorithm is proposed. In the preprocessing step the scanned images of pipe are analyzed and crack features are extracted. In the classification step the neuro-fuzzy algorithm is developed that employs a fuzzy membership function and error backpropagation algorithm. The idea behind the proposed approach is that fuzzy membership function will absorb variation of feature values and the backpropagation network, with its learning ability, will show good classification efficiency.**

***Index Terms*—Backpropagation algorithm, crack features, image processing, neural networks, neuro-fuzzy algorithms, pipe defect classification, pipeline inspection.**

I. Introduction

CLOSED circuit television (CCTV) surveys of underground pipelines are used widely in North America to assess the structural integrity of pipes [1]. CCTV surveys are conducted using remotely controlled vehicle carrying a television camera through an underground pipe. The data acquired from this process consist of videotapes, photographs of specific defects, and a record produced by the technician. Diagnosis of defects depends on experience, capability, and concentration of the operator, making the detection of defect error prone. An automatic underground pipe inspection system is required, based on the scanned images, and which can extract and assess the structural condition of pipes to ensure accuracy, efficiency, and economy of underground pipe examination.

The structural condition of underground pipe is decided by the function of several features of its defects. These defects appear in the form of random-shaped cracks, holes, and others. A number of pattern recognition methods using image processing have been proposed in the literature [2]–[4]. They include approaches based on the edge detection or mathematical morphology analysis and the hybrid method of these two approaches. Most of the literature concerning the detection of defects in civil structure deals with the analysis of pavement and concrete distresses [5], [6], analyzes which are not directly applicable to underground pipe inspection.

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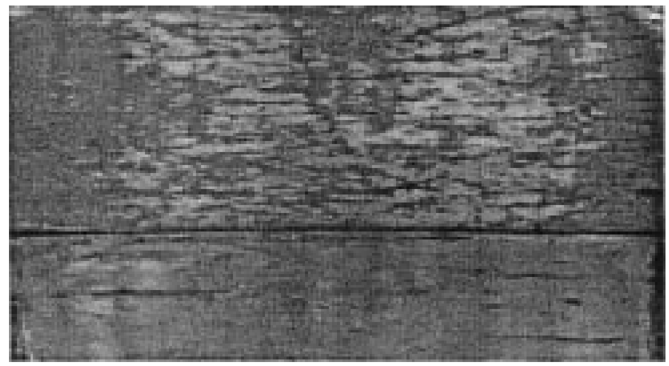

Fig. 1. Typical image of underground pipe surface.

In this paper, a defect detection methodology based on local detection of linear structures and neuro-fuzzy algorithm is proposed. The scanned images are obtained by Pipe Scanner and Evaluation Technology (PSET) camera, developed by CORE Corp., California, and TOA Grout, Japan [7]. Typical scanned image of underground pipe surface is shown in Fig. 1.

II. Underground Pipe 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 camera provides images to an operator who is trained to detect, classify, and rate the severity of defects against documented criteria [8]. The typical CCTV camera and scanning process of underground pipe is shown in Fig. 2. This method of inspection is vulnerable to lapses in operator concentration, inexperience, and the inability of the image to reveal important defects [9]. Thus, diagnosis of defects depends on experience, capability, and concentration of the operator, making the detection of defect error prone.

III. Automated Underground Pipe Defect Detection

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 [10]–[13]. Edge detection plays an important role in a number of image processing applications such as scene analysis and object recognition [14], [15]. Several edge detection algorithms can be found in [16] and [17]. Most of these

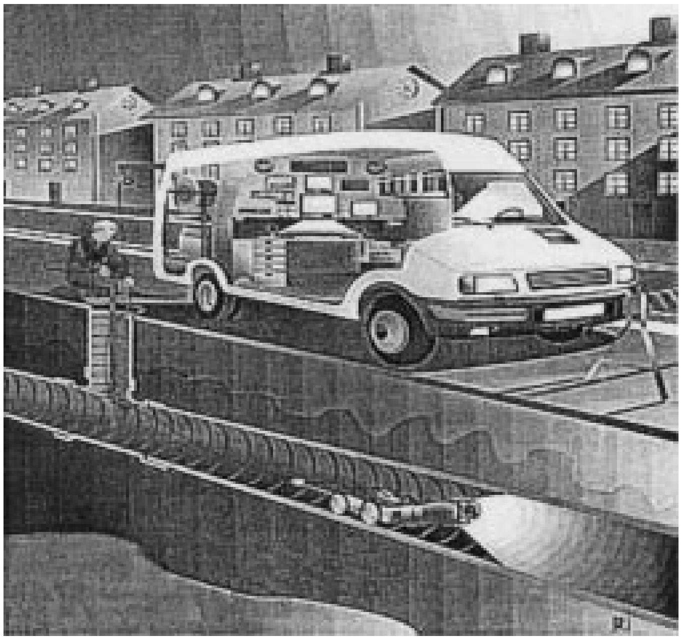

Fig. 2. CCTV camera and underground inspection process.

algorithms may be considered as generalized edge detectors, and they do not take account of the special properties of the objects being detected. These methods cannot be directly employed to detect defects in the underground pipe scanned images. In analyzing underground pipe scanned image data, one needs to consider complications due to the inherent noise in scanning process, irregularly shaped cracks as well as the wide range of pipe background patterns. One of the major problems in detecting cracks that are camouflaged in the background of corroded areas, debris, patches of repair work, and areas of poor lighting conditions.

In the past 20 years, many approaches have been developed to deal with the detection of linear features on optic or radar images [3], [12]. 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 [5], [6]. 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 [15]. Edge detection and line finding techniques, of course, have been studied since the early days of this field and are well documented in textbooks [18]–[20]. However, in spite of the large amount of previous research in this area, and a number of comparative studies [21], [22], the choice of algorithms suitable for detection of defects in the underground pipe images is not clear.

The approach taken in this study for detection of cracks 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 [23], widely used in coherent imagery. An in-depth statistical study of its behavior is given in [24]. The brightness of pixel s is A_s, so the empirical mean μ_i of a given region i having n_i pixels is: $\mu_i = (1/n_i)\sum_{s\in i} A_s$. The response of the edge detector between region i and j is defined as r_{ij}

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

Detector D2 uses the normalized centered correlation between two populations of pixels. This approach is inspired from the work of Yakimovsky [25]. The ideal crack best approximating the amplitude in a given window Wx_0 around a pixel x_0 and for a given direction $d_k (k \in \{1, \ldots, N_d\})$ is computed using the Yakimovsky's operators. The operators of Yakimovsky assume that edges are interfaces between sets of points, each set being described by a normal distribution. The mathematics for distribution parameter comparison is used to form a function of crack strength in an area, and is expressed as

$$s = \left[\frac{\left(\sigma_0^2\right)^{m+n}}{\left(\sigma_1^2\right)^m \left(\sigma_2^2\right)^n}\right] \tag{2}$$

where

$$\begin{aligned}
\sigma_0^2 &= \text{Variance for regions 1, 2, and 3 taken together}\\
&= \frac{\left\lfloor m\sigma_1^2 + n\sigma_2^2 + m(\mu_0-\mu_1)^2 + n(\mu_0-\mu_2)^2\right\rfloor}{(m+n)}.\\
\mu_0 &= \text{Mean for regions 1, 2, and 3 taken together}\\
&= (m\mu_1 + n\mu_2)/(m+n).\\
m, \mu_1, \sigma_1^2 &= \text{Samples, mean, variance for region 1.}\\
n, \mu_2, \sigma_2^2 &= \text{Samples, mean, variance for regions 2 and 3.}
\end{aligned}$$

A pixel is considered as belonging to a crack when its response s is large enough, i.e., higher than some *a priori* chosen threshold $s_{\min}$. Once this ideal crack is defined, the validity of the hypothesis "there is a crack in x_0 with the direction d_k" is tested by using the normalized centered cross correlation between pixels of Wx_0 and the ideal crack. The cross-correlation coefficients ρ_{ij} can be shown to be

$$\rho_{ij}^2 = \frac{1}{1 + (n_i + n_j) * \dfrac{n_i\gamma_i^2 c_{ij} + n_j\gamma_j^2}{n_i n_j (c_{ij}-1)^2}} \tag{3}$$

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 (ratio of standard deviation and mean) that adequately measures homogeneity in underground pipe images. This expression depends on the contrast between regions i and j, but also takes into account the homogeneity of each region, thus being more coherent than the ratio detector (which may be influenced by isolated values). The crack detector D2 is defined by the minimum response ρ (cross-correlation coefficients) of the filter on both sides of the structure $\rho = \min(\rho_{12}, \rho_{23})$. A crack is detected when the response is higher than the decision threshold $\rho_{\min}$.

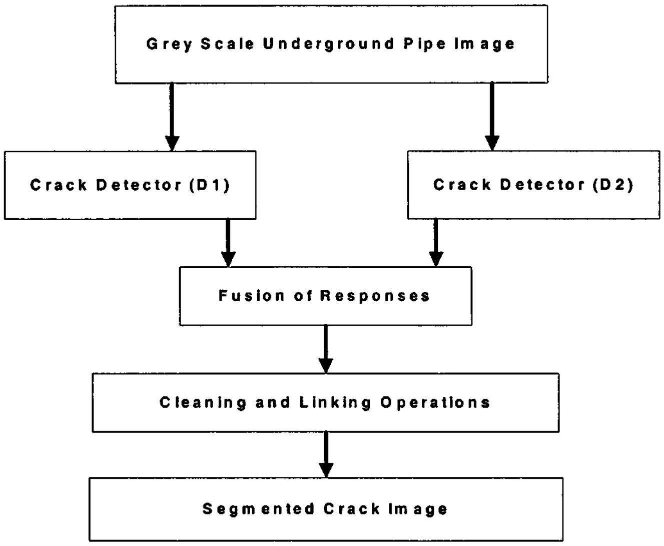

Fig. 3. Diagram showing the different steps for detection of crack features.

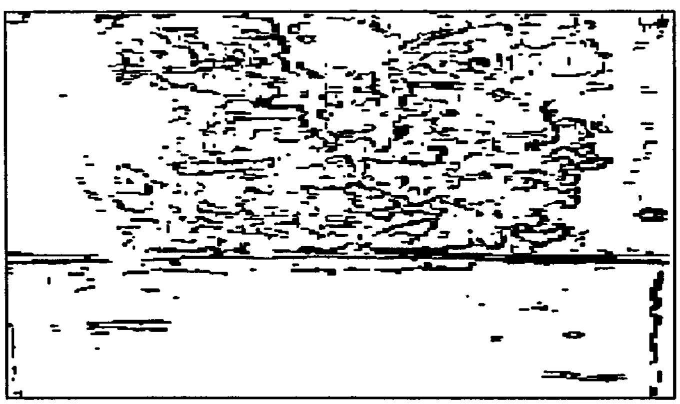

Fig. 4. Thresholded responses of the crack detectors for multiple cracks.

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 postprocessed to provide candidate segments. Fig. 3 shows the diagram for different steps of the proposed method. Threshold response of the line detectors after fusing and linking operations is shown in Fig. 4. The crack features detected in the image will be later used for feature extraction and classification.

IV. Feature Extraction of Pipe Defects

Feature extraction is an important stage for any pattern recognition task especially for pipe defect classification, since pipe defects are highly variable and it is difficult to find reliable and robust features. According to the study in [26], trained operators mainly rely on five criteria in visual interpretation of images. These are intensity, texture, size, shape, and organization. The intensity corresponds to the spectral features, which can generally be extracted easily. Textural features are those characteristics such as smoothness, fineness, and coarseness or certain pattern associated with an image [27]. They reflect the local spatial distribution property in a certain region. The spectral and textural features are most widely used in automatic object classification. Other features such as size, shape, and organization information attribute to the large scale or global spatial distribution.

Generally, two broad categories of object features are most commonly used in the material/pavement classification field [28]: shape and textural features. The first class of features, which plays a more important role for object classification, extracts the information based on the geometric shape of the object. Some of the most commonly used methods in this category include area, length, roundness, etc. The second category, i.e., textural features, distinguish objects by using statistical measures based on gray-scale co-occurrence matrix [29] and its variant, such as gray-scale difference vector, moment invariants, and gray-scale difference matrix. The salient features of the data can also be extracted through a mapping, such as Fourier transform, discrete cosine transform, Karhunen–Loeve transform, or principal component method [30], from a higher dimensional input space to a lower dimensional representation space.

Depending on the analyzed parameters or features of each object, the most suitable set of features that represents the characteristics of each object in the underground pipe images is selected. We have used information based on the geometric shape and size of the objects present in the underground pipe images for feature extraction. The advantages of the proposed extraction of geometrical features from the image are its capability to quantify distress features in terms of understanding parameters (area, lengths, roundness, etc.) and its ability to classify the segmented image based on such quantities. These features constitute the input parameters for the classifier.

The five features selected for classification of the type of the cracks in the pipe image are: 1) area; 2) number of objects; 3) major axis length; 4) minor axis length; and 5) projection and then taking mean and variance in each of the four projected directions (0°, 45°, 90°, and 135°). Each segmented crack image is to be classified into one of the following seven classes. They are based on the extracted 12 feature vectors, which describes the existence and orientation of crack segments and severity of holes present in the image: 1) transverse crack; 2) longitudinal crack; 3) diagonal crack; 4) multiple crack; 5) mushroom crack; 6) minor hole; and 7) major hole.

V. Underground Pipe Defects 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 $\boldsymbol{A}$, then it gives a penalty $\boldsymbol{f}$ to the decision, if the total area of crack is $\boldsymbol{B}$, then it gives a penalty $\boldsymbol{g}$ to the decision, if a pipe has $\boldsymbol{f}, \boldsymbol{g}, \ldots, \boldsymbol{k}$ 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.

The classification of underground pipe defects is carried out using Euclidean distance method, Fuzzy K-NN algorithm, conventional backpropagation neural network, and neuro-fuzzy algorithm. The theoretical backgrounds of all classifiers are presented and their relative advantages are discussed.

A. Defect Classification Based on the Euclidean Distance

In conventional recognition methods, the Euclidean distance has been commonly used as a distance measure between two vectors. The Euclidean distance d is defined by [31]

$$d = \left(\sum_{i=1}^{L} (X_i - R_i)^2 \right)^{1/2} \tag{4}$$

where X_i and R_i represent the ith component of the input and reference feature vectors, respectively, and L denotes the total number of features.

B. Defect Classification Based on the Fuzzy K-NN Algorithm

Reference [32] introduced the theory of fuzzy sets. It is based on the simple idea of introducing a degree of belonging of an element to a specific set. The relationship between fuzzy sets and classification is based on the fact that most real-world classes are fuzzy in nature. Thus, given an object p and a cluster C, the basic question is not whether p is a member of C, but the degree to which p belongs to C, i.e., grade of membership of p in C [33]. In conventional classification techniques an object is assigned to one and only one of the classes, with a degree of membership equal to one, assuming well-defined boundaries between classes, while in fuzzy pattern recognition an observation can belong to more than one class in different degrees. This is very important in pattern recognition where the membership of an element in a certain group is usually not clear.

The fuzzy K-NN algorithm is considered one of the most accurate algorithms in pattern recognition [34]. The classical (crisp) K-NN algorithm classification rule assigns an input sample vector y, which is of unknown classification, to the class that is represented by a majority amongst its K-nearest neighbors [35]. The K-nearest neighbors are chosen from a labeled data sample (data of known classification). The fuzzy K-NN algorithm assigns class membership to a sample observation based on the observation distance from its K-nearest neighbors and their membership [36]. The fuzzy K-NN algorithm is described in detail elsewhere [37].

C. Defect Classification Using Artificial Neural Networks

An artificial neural networks (ANNs) attempt to mimic, in a very simplified way, the human mental neural structure and functions [38]. It can be characterized as a massively parallel interconnection of simple neurons that function as a collective system. The network topology consists of a set of nodes (neurons) connected by links and usually organized in a number of layers. Each node in a layer receives and processes weighted inputs from nodes in the previous layer and transmits its output to nodes in the following layer through links. Each link is assigned a weight that is a numerical estimate of the connection strength. The weighted summation of inputs to a node is converted to an output according to a transfer function (typically a sigmoid function). Most ANNs have three layers or more: an output layer, which is used to produce an appropriate response to the given input; and one or more intermediate layers, which are used to act as a collection of feature detectors [39]. 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. More information about neural networks can be found in [40].

Among the well-known and commonly used neural networks is the multilayer perceptron (MLP) [41], which uses the supervisory learning paradigm. In general, an MLP consists of a fully interconnected computational unit called neurons, or nodes, organized in the form of layers. An MLP can be regarded as a mapping from an input space R^n to an output space R^m. If layer 0 denotes the input layer, then the output $y_i^{(l)}$ of the ith node of layer l is given by

$$y_i^{(l)} = \sigma^{(l)} \left(\sum_{j=1}^{P(l-1)} \upsilon_{ij}^{(l)} y_j^{(l-1)} + \theta_i^{(l)} \right) \qquad i = 1, \ldots, P^{(l)},\ l = 1, \ldots, L \tag{5}$$

where

$\sigma^{(q)}(\cdot)$	activation function of layer q;
$P^{(q)}$	number of nodes in layer q;
$\upsilon_{ij}^{(q)}$	weight connecting the jth node of layer $q-1$ with the ith node of layer q;
$\theta_i^{(q)}$	bias of the ith node in layer q;
L	total number of layers excluding the input layer.

Although the output layer's activation function $\sigma^{(L)}(\cdot)$ is usually chosen to be linear, hidden layers may take many sorts of activation functions $\sigma^{(l)}(\cdot)$, $l = 1, \ldots, L-1$. If the MLP contains one hidden layer, then $L = 2$. If its activation function is taken as the hyperbolic tangent sigmoid function, it can be expressed as

$$\sigma^{(1)}(x) = \frac{2}{1 + e^{-2x}} - 1. \tag{6}$$

The neural-network universal approximation property guarantees that any sufficiently smooth function can be approximated using a two-layer neural network [42].

D. Neuro-Fuzzy Systems

Neuro-fuzzy systems belong to a newly developed class of hybrid intelligent systems, which combine the main features of artificial neural networks with those of fuzzy logic [43]. The goal here is to circumvent difficulties encountered in applying fuzzy logic for systems represented by numerical knowledge (data sets), or in applying neural networks for systems represented by linguistic information (fuzzy sets). Neither fuzzy reasoning systems nor neural networks are by themselves capable of solving problems involving at the same time both linguistic and numerical knowledge [44]. Connotations and definitions provided in the literature to describe *neuro-fuzzy* systems have increased substantially over the last few years. In [45] for instance, neuro-fuzzy systems are described as hybrid systems. A number of researchers have used this term to depict systems that involve in some ways both fuzzy logic and neural networks features. According to [46], there exist five classes (categories) of neuro-fuzzy systems.

- **Class A:** This class includes systems that have the same topology as classical neural networks, but instead of having the numerical (standard) neuron, they employ the fuzzy neuron.
- **Class B:** This class includes adaptive fuzzy systems that utilize neural networks for training the fuzzy system to update the fuzzy rules or the membership functions.
- **Class C:** This class involves classical neural networks, for which the learning is achieved through fuzzy systems-based functions, that is, by using fuzzy methods to update the weights of the neurons.
- **Class D:** Systems in this class are created by using a structure involving independent fuzzy systems and neural networks components.
- **Class E:** This class is a mixture of classical systems and any system from the above classes.

In our study we will use a special structure of class E, where the input and the output of the ANN is a fuzzy entity. Fuzzy neural networks such as the ones proposed in this study provide more flexibility in representing the input space by integrating vagueness usually associated with fuzzy patterns with learning capabilities of neural networks. In fact, by using fuzzy variables as input to the neural network structure, the boundaries of the decision space become represented in a less restrictive manner (unlike the conventional structure of neural networks where the input are required to be crisp), and permits the representation of data possibly belonging to overlapping boundaries. As such more information could be represented without having recourse to the storage of huge amount of data, which are usually required for training and testing of conventional "crisp-based data training" neural network. A well-known model proposed by Pal and Mitra [47] introduced fuzzy concepts into backpropagation networks for fuzzy pattern classification, and the reader may wish to consult their article [47]. Similar steps were utilized here for the training and testing of our proposed fuzzy-based neural network. This is described next.

E. Defect Classification Using the Proposed 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. For example, the fuzzy concept was used to change the learning rate or momentum factor [48]. This algorithm was efficient to overcome the local minima problem with reduced computational complexity. We apply this scheme to underground pipe defect classification, however, it does not increase the classification rate. Thus, we apply the fuzzy concept simply in converting feature values into fuzzified data, which are inputs and outputs to the backpropagation neural-network algorithm. More advanced neuro-fuzzy classifiers for the considered domain, e.g., systems

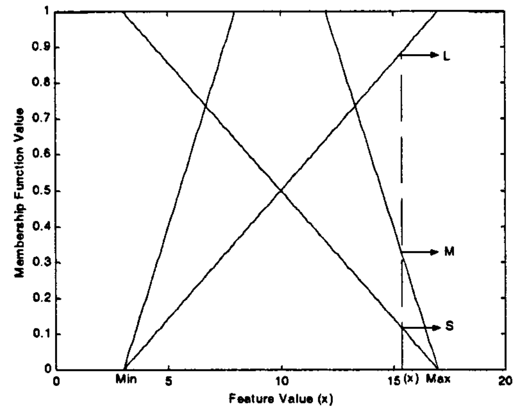

Fig. 5. Linguistic representation of feature values by trapezoidal membership function.

that are able to synthesize fuzzy-rule-based knowledge from data, may be considered in our future work.

1) Input Pattern Representation in Linguistic Form: In the proposed neuro-fuzzy algorithm we use the fuzzy data as inputs to a neural network structure. Sometimes, variation of feature values is large, and then it is difficult to recognize faces correctly based on these feature values. To solve this problem, we first convert each defect feature value into three fuzzy data, and then learning is performed with this fuzzy data set using the backpropagation algorithm. Finally, we classify defects using the backpropagation algorithm.

There are several types of membership functions in representing fuzzy phenomena. The proposed crack classification algorithms are simulated using triangular, trapezoidal, and Gaussian membership functions. To convert 12 normalized features into 36 fuzzy data, we determine the MAX and MIN values that are the maximum and minimum feature values for entire dataset, respectively. As shown in Fig. 5, we generate three membership functions denoted by "S" (small), "M" (medium), and "L" (large). Note that these membership functions are specified by MIN and MAX, as shown in Fig. 5. Then we compute three fuzzy data for each feature value and use these data as the input values to neural networks. In Fig. 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. In the crack classification method using trapezoidal membership function, the five features are represented by means of linguistic variables specified by a trapezoidal membership function as shown in Fig. 5. The triangular and Gaussian membership function, as shown in Figs. 6 and 7, locates at the average value of features of the same image, and has a maximum value of one over the limited range that is specified by the standard deviation of the feature value. To generate a linguistic variable we first compute the average and standard deviation of the feature values of the image. Then we uniformly divide the interval between MIN and MAX 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

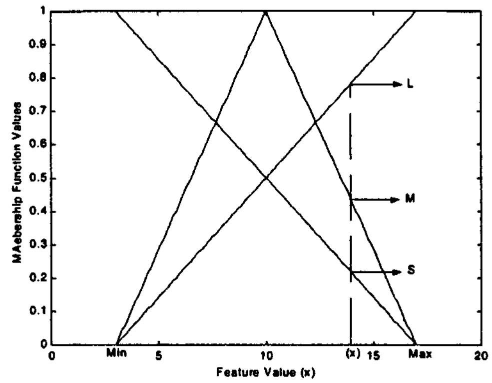

Fig. 6. Linguistic representation of feature values by triangular membership function.

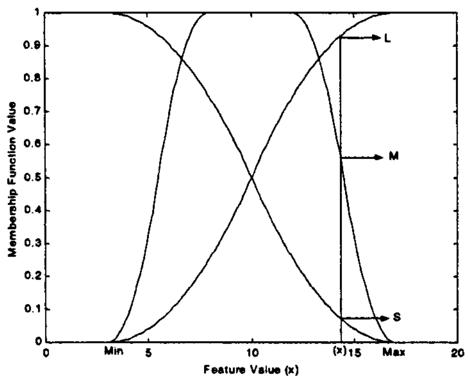

Fig. 7. Linguistic representation of feature values by Gaussian membership function.

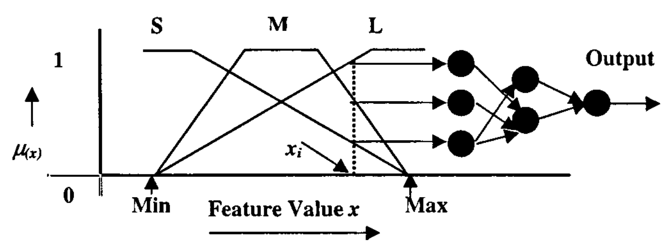

Fig. 8. The neuro-fuzzy neural network architecture with fuzzy inputs.

width at the top of the trapezoidal and Gaussian membership function is set to σ_i, where σ_i denotes the standard deviation of the ith feature value. Note that for input data greater (smaller) than MAX (MIN) we clip the membership value to 1 (0). These membership functions for images are stored in a database for neural network learning. The neuro-fuzzy neural architecture with fuzzy inputs is shown in Fig. 8.

2) Output Class Representation in Linguistic Form: In this approach, the conventional neural network is manipulated only at the output layer level with the fuzzy desired output. In general, the multilayer perceptron (MLP) neural network passes through two phases, training and testing. During the training phase, supervised learning is used to assign the output membership values ranging in [0, 1] to the training input vectors. Each output from MLP may be assigned with a nonzero membership instead of choosing the single node with the highest activation. It allows modeling of the fuzzy data when the feature space involves overlapping pattern classes, such that a pattern

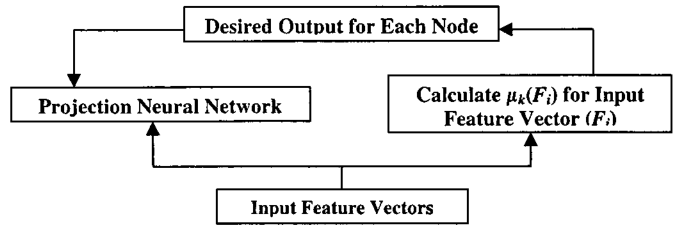

Fig. 9. The training for the neuro-fuzzy neural network with fuzzy outputs.

point may belong to more than one class with a nonzero membership. During training, each error in membership assignment is fed back and the connection weights of the network are appropriately updated. The backpropagated error is computed with respect to each desired output, which is a membership value denoting the degree of belongingness of the input vector to a certain class. The testing phase in fuzzy MLP is equivalent to the conventional MLP.

In the case of m-class problem with n-dimensional feature space, let the n-dimensional vectors O_{kj} and V_{kj} denote the mean and the standard deviation for jth input feature respectively of the numerical training data for the kth class. The weighted distance, Z_{ik}, of the training pattern vector $\vec{F_i}$ from the kth class is defined as

$$Z_{ik} = \sqrt{\sum_{j=1}^{n} \left[\frac{F_{ij} - O_{kj}}{V_{kj}}\right]^2} \quad \text{for } k = 1, \ldots, m \quad \text{and} \quad j = 1, \ldots, n \tag{7}$$

where F_{ij} is the value of the jth input feature component of the ith pattern point. The weight $1/V_{kj}$ is used to take care of the variance of the classes so that a feature with higher variance has less significance in characterizing a class. The membership of the ith pattern to class C_k is defined as follows:

$$\mu_k\left(\vec{F_i}\right) = \left(\frac{Z_{ik} - \min\limits_k(Z_{ik})}{\max\limits_k(Z_{ik}) - \min\limits_k(Z_{ik})}\right) \quad \text{for } k = 1, \ldots, m. \tag{8}$$

Obviously $\mu_k(\vec{F_i})$ lies in the interval [0, 1]. Here, the larger the distance of a pattern from a class, the lower its membership value to that class. Except for the fuzzy membership desired values in the output layer, the training method and network structure is equivalent to the conventional MLP classifier. The training scheme for fuzzy output neural network is shown in Fig. 9.

3) Fuzzy Input and Output Module and Neural Network Module: The concept of the proposed fuzzy input and output module and neural network module is illustrated in Fig. 10. The fuzzy ANN model has three modules: the fuzzy input module, the neural network module, and the fuzzy output module. The neural network module is a conventional feedforward artificial neural network. A simple three-layer network with a backpropagation training algorithm is used in this study. To increase the rate of convergence, a momentum term and a modified backpropagation training rule called the delta–delta rule [49] are used. The input layer of this network consists of

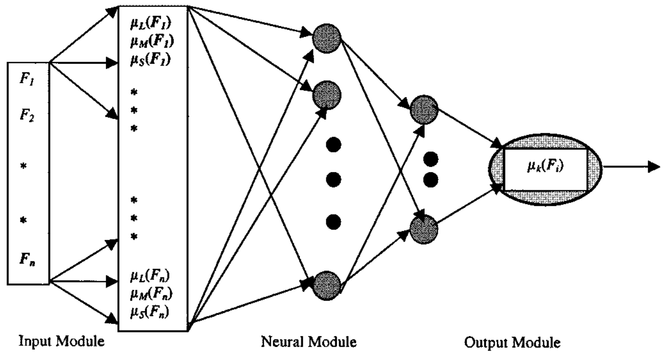

Fig. 10. The proposed neuro-fuzzy neural-network architecture.

36 nodes (because of the use of fuzzy sets to screen the 12 input variables; discussed in the previous Section V-E1), and the output layer consists of seven nodes (trained with fuzzy output values; discussed in the previous Section V-E2). As shown in Fig. 10, the input layer of this fuzzy ANN model is actually an output of the input module. On the other hand, the output layer becomes an input to the output module. The input and output modules, for preprocessing and postprocessing purposes, respectively, are designed to deal with the data of the ANN using fuzzy sets theory. Experimental results from all the above methods are presented in the following section.

VI. Experimental Results and Discussions

In this section, the proposed underground pipe defect classification system is examined on the CCTV scanned image data set. This data set and the process of labeling are first introduced. The neural-network structure, training scheme, and validation processes are also described. In order to select the most suitable network architecture, various neural-network paradigms are tested. Finally, various classification schemes are implemented and the final results are provided.

A. Underground Pipe Scanned Images

The pipe data analyzed in this study was obtained from the CCTV survey of sewer pipes in 12 major cities across North America. The data acquired from this process consist of videotape, digitized images on CD-ROM, few photographs of specific defects, and a record produced by the technician classifying each defects according to the various levels of deterioration. Since the ground truth was not available for all the defects and moreover it was not reliable, five trained pipeline operators from city of Toronto were asked to identify all possible defect types as well as the background areas based on the visual inspection and other related information. This was accomplished with the aid of a computer software package developed solely for this purpose.

B. Neural-Network Structure, Training, and Validation

Neural network structure represents the learning algorithm and the neural-network architecture. The learning algorithm is the heart of the neural network because it specifies how to modify the connections weights in order to improve the performance of the ANN. Backpropagation algorithm was selected because it is the most widely used learning algorithm [50]. The architecture of the neural network defines the preceding and succeeding nodes for each node in the network. Network architecture includes identifying the number of layers, the number of nodes in each layer, and the connection scheme between the nodes of different layers.

The number of hidden layers should be selected to satisfy three concepts. The first concept is that as the number of hidden layers increases the network speed of learning increases [51]. If the number of hidden nodes is insufficient, the network may not learn or may learn only after a long time (i.e., convergence becomes difficult to achieve). The second concept is that as the number of hidden layers and node increases, the network behavior tends to "remember" the specific patterns rather than generalizing the learning process. "Remembering" particular patterns contradicts the principle generalization of neural networks. The third concept is that as the number of hidden nodes increases the connection weight becomes more difficult to estimate from the training sets. To deal with these issues, a sensitivity analysis has been conducted on the number of hidden layers and nodes required in each hidden layer. The objective of this analysis is to select the minimum number of hidden layers and nodes in each hidden layer that are sufficient to train the network.

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 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. In order to obtain a reliable assessment of the proposed classifier, cross-validation resampling method is applied. The method of cross-validation (also referred to in the literature as the leave-one-out method or the U method) was made popular principally due to the work of Lachenbruch and Mickey [52]. Cross-validation treats $n-1$ out of the n training vectors as a training set. It determines the discriminant functions based on these $n-1$ vectors and then applies them to classify the one vector left out. This is done for each of the n training vectors and the misclassification rate estimate is simply the fraction of the n vectors incorrectly classified. The leaving-one-out error estimation technique is a special case of the general class of cross-validation error estimation methods [53]. In k-fold cross-validation, the cases are randomly divided into k mutually exclusive test partitions of approximately equal size. The cases not found in each test partition are independently used for training, and the resulting classifier is tested on the corresponding test partition. The average error rate over all k partitions is the cross-validated error rate. For this study, ten-fold cross-validation seemed to be adequate and accurate, particularly for the sample size of 840 where leaving-one-out is computationally expensive.

To select the appropriate architectural for each network, a sensitivity analysis has been conducted. The analysis involves training each network using different architectures (i.e., the number of nodes in the hidden layer) and calculating the corresponding reliability level. The appropriate architecture for

TABLE I
CLASSIFICATION RATE OF NETWORK BY FUZZY MEMBERSHIP FUNCTIONS

Fuzzy Input	Membership Function	Fuzzy Output	Classification Rate (%)
Yes	Triangular	No	86.9
		Yes	88.5
	Trapezoidal	No	89.6
		Yes	91.5
	Gaussian	No	91.1
		Yes	92.7
No	No	Yes	87.3

TABLE II
CLASSIFICATION RATE BY VARIOUS METHODS

Classification Method		Classification Rate (%)
Euclidean Distance Method		81.1
Fuzzy K-Nearest Neighbor Method		83.2
Backpropagation Neural Network		85.9
Neuro-Fuzzy Algorithm	Fuzzy Input	91.1
	Fuzzy Output	87.3
Fuzzy Input and Output Neural Network		92.7

a network is the one that yields the highest reliability level and has the minimum number of nodes in the hidden layer.

The neurofuzzy algorithm as described earlier and as been presented originally in the work of Pal and Mitra [47] is implemented. The first step is to provide the weighted distances of the training patterns from the corresponding class as presented in equation (7). The degree of belonging of the ith pattern in the class k is then defined according to equation (8). There are several types of membership functions in representing fuzzy phenomena. The proposed crack classification algorithms are simulated using triangular, trapezoidal, and Gaussian membership functions. Table I shows the performance of neuro-fuzzy network by using different membership functions. Compared to Gaussian membership function, Triangular and Trapezoidal functions did not achieve high classification accuracy owing to the straight-line nature of membership function as compared to smooth curve for Gaussian.

C. Comparison Study for Different Classifiers

For performance comparison with the proposed neuro-fuzzy algorithm, we simulate several conventional algorithms such as the Euclidean distance method, the Fuzzy K-NN algorithm, and the backpropagation algorithm. The extracted underground pipe defect features were used for this comparison. The classification output by various methods is shown in Table II. It can be seen there that the proposed neuro-fuzzy algorithm using a Gaussian membership function yields better recognition results than the Euclidean distance method, Fuzzy K-NN method, and conventional backpropagation algorithm. In general, the neuro-fuzzy algorithm performed slightly better and produced more consistent results than the conventional backpropagation algorithm. The overall classification rate has increased from 85.9% to 92.7%. The result is not surprising given that the neuro-fuzzy algorithm takes the best features out of the fuzzy based description in one hand and the data collected for training neural network in the other hand.

VII. CONCLUSION

In this study we propose an underground pipe defect classification using a neuro-fuzzy algorithm that combines under an appropriate scheme the capabilities of the backpropagation algorithm and the fuzzy representation concept. Fuzzy sets are used in the input module as well as in the output module to "screen" data patterns before network training. With this technique, the proposed network can be trained with greater efficiency. In the feature extraction step we extract five normalized features, based on image processing techniques and these features values are then fuzzified and applied to the backpropagation algorithm in the recognition step. We show simulation results of the proposed neuro-fuzzy algorithm in comparison to the Euclidean distance method, Fuzzy K-NN method, and conventional backpropagation algorithm. The results show that the proposed neuro-fuzzy algorithm using a Gaussian membership function gives better recognition results than the conventional methods. The results show the promise of the proposed fuzzy-neural structure as a tool for classifying defects in underground pipe scanned images. Future work should include searching for a new powerful and robust feature extraction scheme for the neuro-fuzzy network to accommodate significant background pattern and temporal changes in scanned pipe imagery sequences.

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