Automation in Construction 15 (2006) 73 – 83

AUTOMATION IN CONSTRUCTION

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Neuro-fuzzy network for the classification of buried pipe defects

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Accepted 4 February 2005

Abstract

Pipeline infrastructure is decaying at an accelerating rate due to reduced funding and insufficient quality control resulting in poor installation, little or no inspection and maintenance, and a general lack of uniformity and improvement in design, construction and operation practices. The current practice that is being followed to inspect the conditions of pipes is usually time consuming, tedious and expensive. It may also lead to diagnostic errors due to lack of concentration of human operators. Buried pipe defect classification is thus a practical and important pattern classification problem. These defects appear in the form of randomly shaped cracks and holes, broken joints and laterals, and others. This paper proposes a new neuro-fuzzy classifier that combines neural networks and concepts of fuzzy logic for the classification of defects by extracting features in segmented buried pipe images. A comparative evaluation of the K-NN, fuzzy K-NN, conventional backpropagation network, and proposed neuro-fuzzy projection network classifiers is carried out. Among the five neural methods implemented and tested, the proposed neuro-fuzzy classifier performs the best, with classification accuracies around 90% on real concrete pipe images.

Keywords: Pipeline infrastructure; Automated inspection; Image processing; Segmentation; Features; Neural network; Backpropagation network; Neuro-fuzzy projection network

1. Introduction

Feature extraction and object classification are important areas of research and of practical applications in a variety of fields including pattern recognition, artificial intelligence, statistics, cognitive psychology, vision analysis, and medicine [1–8]. Over the last 25 years, extensive research has taken place in the development of efficient and reliable methods for the selection of features in the design of pattern classifiers, where the features constitute the inputs to the classifier. The quality of this design depends on the relevancy, discriminatory power and ease of computation of various features. Another important issue in object classification is the choice of an appropriate classifier. There are at least two types of classifiers: traditional classifiers (e.g., linear discriminant, maximum likelihood, k-nearest neighbor, etc.) [9] and neural based classifiers (e.g., backpropagation, projection network, self-organizing map, adaptive resonance theory, etc.) [10].

Given a digitized pipe image containing several objects, the pattern recognition process consists of three major phases, as shown in Fig. 1. The goal of this paper is to apply methods of feature extraction and several classifications to buried pipes, a problem of considerable practical and research interest [11]. Chae and Abraham [14] employed image preprocessing, classification through a neural network, and defect identification using a fuzzy estimator. Moselhi and Shehab-Eldeen [12,13] classified pipe defects through a conventional backpropagation neural network trained with feature vectors as inputs. Automated real-time pavement distress detection using fuzzy logic and neural networks was studied using fuzzy homogeneity for image enhancement and feature extraction [15]. A methodology for automated pavement crack detection [16] demonstrated the potential of using neural network for classification and quantification of cracking on

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doi:10.1016/j.autcon.2005.02.005

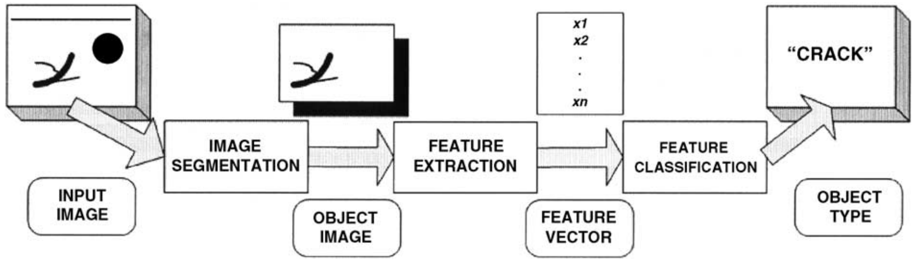

Fig. 1. The three phases of pattern recognition.

pavement, and it requires further improvement of the image segmentation.

We have previously demonstrated morphological [17] and statistical [18] approaches to segmenting images of underground concrete pipes, an important precursor step to this paper. The proposed morphological approach is effective at segmenting joints, laterals and pipe background, as in Fig. 2, and the statistical approach is effective at segmenting cracks from pipe images, as in Fig. 3.

Although the developed methods were effective at segmentation, they did not assess the severity or extent of distress, a more subtle question, but one of crucial importance in pipe infrastructure assessment. The purpose of this paper is to propose and develop a neuro-fuzzy classifier which is able to classify the severity of distress in cracks, holes, laterals, joints, and pipe collapse. Our approach combines a fuzzy membership function with a projection neural network where the former handles feature variations and the latter leads to good learning efficiency.

2. Feature extraction

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. Trained operators mainly rely on five criteria [19] in the visual interpretation of images: intensity, texture, size, shape, and organization. Intensity corresponds to spectral features, which can generally be extracted easily. Textural features are those characteristics such as smoothness, fineness, or coarseness associated with an image [20], reflecting local spatial properties. Other features such as size, shape, and organization associate with large scale or global spatial distribution.

Shape and textural features are most commonly used in the material/pavement classification field [16]. Some of these common shape features include area, length, roundness, and morphology. Textural features distinguish objects by using statistical measures such as gray-scale co-occurrence matrices [21] and variants, such as gray-scale difference vectors, moment invariants, and gray-scale difference matrices. The salient features of the data can also be extracted through a mapping, such as Fourier transform, Hough transform, Karhunen–Loeve transform, or principal components [22], from a higher dimensional input space to a lower dimensional representation space. Because pipe-image texture is largely dominated by pipe discoloration and background patterning, which are largely

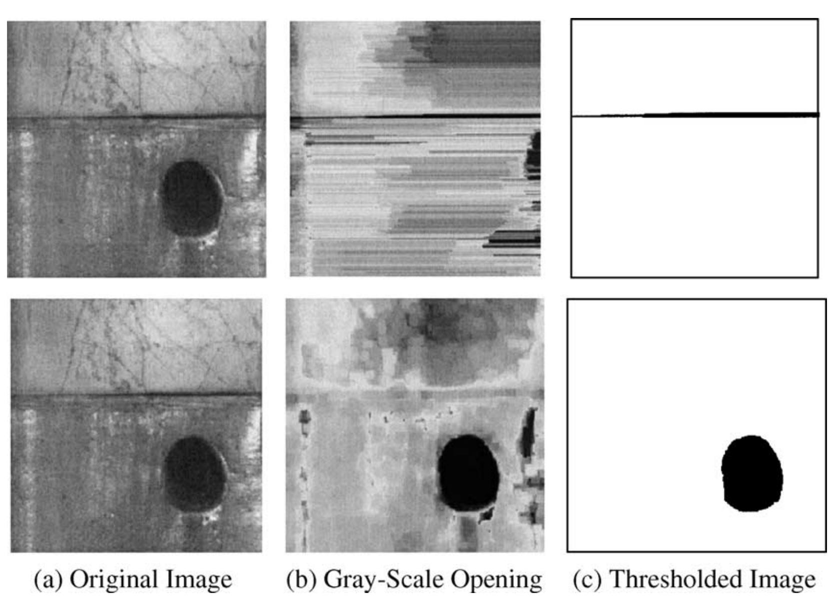

Fig. 2. An illustration of morphological segmentation, from [17], identifying a joint (top) and lateral (bottom).

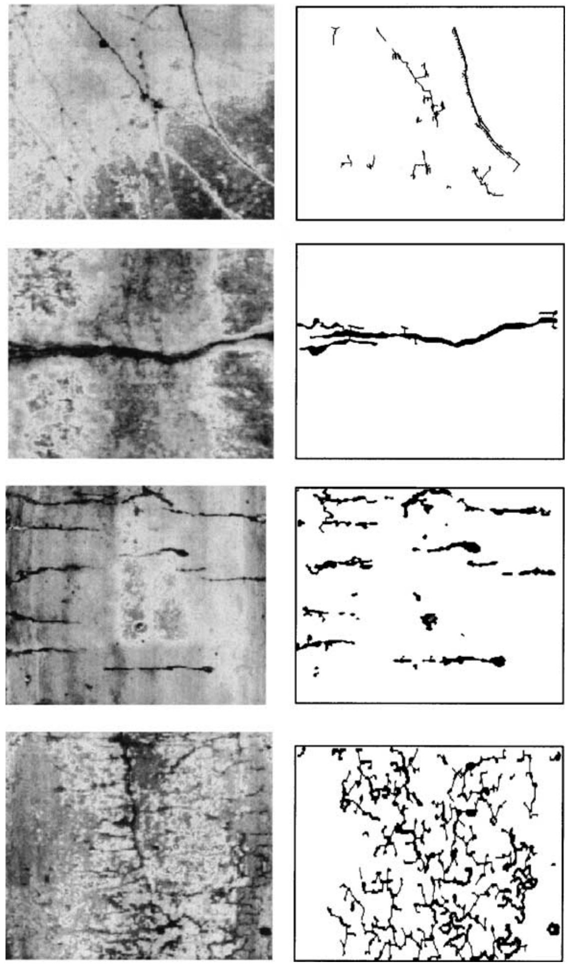

Fig. 3. An illustration of statistical crack extraction, from [18], showing different pipe surface crack patterns.

unrelated to pipe distress, we focus on information of geometric shape and size 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 intuitive parameters (area, length, roundness, etc.) and its ability to classify the segmented image based on such quantities. Because the objects in the image are pre-segmented by type [17,18], we can select features specialized by distress type, discussed in the following sections.

2.1. Selection of crack and hole features

In the present case for classification of the severity of cracks and holes, if the attributes are selected to be the major/minor axis length, and area, then the classifier can be trained for classifying different objects based on their geometry. For example, if an object has a width (minor axis length) of a few millimeters and its length (major axis length) is much greater than its width, then the object can be classified as a crack. On the other hand, if the ratio of major and minor is close to 1 and its minor axis length is a few centimeters, and then the object can be classified as a hole rather than a crack. We also compute the mean and variance of four directional projections, summing the image pixels horizontally, vertically, and along two diagonals. The image projections allow crack discrimination based on orientation (longitudinal vs. transverse vs. mushroom crack). The five features selected for classification of the type of the crack and hole in the underground pipe image are:

1. Area
2. Number of objects
3. Major axis length
4. Minor axis length
5. Mean and variance of image projections (0°, 45°, 90°, and 135°)

Each segmented crack/hole image is to be classified into one of the following seven classes based on the extracted 12 feature vectors:

1. Transverse crack
2. Longitudinal crack
3. Diagonal crack
4. Multiple crack
5. Mushroom crack
6. Minor hole
7. Major hole

2.2. Selection of joint features

We have selected five features based on the shape and size of the underground pipe joints. These features are:

1. Area
2. Number of objects
3. Elongation (ratio of major to minor axis length)
4. Extent (ratio of net area to bounding rectangle area)
5. Mean and variance of image projections (0° and 90°)

An image of a segmented joint is to be classified into one of the following three classes based on the extracted eight feature vectors:

1. Perfect joint
2. Eroded joint
3. Misaligned joint

2.3. Selection of lateral features

Because underground pipe laterals are more-or-less circular in shape, having features which recognize deviations from circularity is key to classifying lateral distress.

There are a wide variety of shape descriptors available [22]. Widely used is the ‘form-factor’ 4π Area/Perimeter^2, which is 1.0 for a perfect circle, and larger for any other shape. A second shape parameter is ‘roundness’, similar to form-factor, calculated as $4*\text{Area}/\pi*\text{Length}^2$, which is 1.0

for a perfect circle. However rather than perimeter, roundness uses the length (longest chord) of the feature, making it more sensitive to shape elongation, rather than how irregular its outline may be. Another shape parameter measures convexity; the 'aspect ratio' of an object, the ratio of the maximum diameter to the minimum diameter, again ignores local smoothness and provides a second measure of elongation. We have selected five features to discriminate and classify pipe laterals:

1. Area
2. Number of objects
3. Roundness
4. Form-factor
5. Aspect ratio

A segmented lateral is to be classified into one of the following three classes based on the extracted five feature vectors:

1. Perfect lateral
2. Eroded lateral
3. Collapsed lateral

3. Pattern classification

Pattern recognition can be defined generally as the allocation of objects to classes so that individual objects in one class are as similar as possible to each other and as different as possible from objects in other classes. Clearly, the more a priori information that is known about the problem domain, the more the classification algorithm can be made to reflect the actual situation. For example, if the a priori probabilities and the state conditional densities of all classes are known, then Bayes decision theory produces optimal results in the sense that it minimizes the expected misclassification rate [2]. However, in many pattern recognition problems, the classification of an input pattern is based on data where the respective sample sizes of each class are small and possibly not representative of the actual probability distributions, even if they are known. In these cases, many techniques rely on some notion of similarity or distance in feature space, for instance, clustering and discriminant analysis [23].

3.1. Fuzzy sets

Fuzzy sets were introduced by Zadeh in 1965 [24]. Since that time, researchers have found numerous ways to utilize this theory to generalize existing techniques and to develop new algorithms in pattern recognition and decision analysis [22,23,25–27]. In [25] Bezdek suggests that interesting and useful algorithms could result from the allocation of fuzzy class membership to the input vector, thus affording fuzzy decisions based on fuzzy labels. Bezdek's work is concerned with incorporating fuzzy set methods into the classical *K*-NN decision rule. In particular, a 'fuzzy *K*-NN' algorithm has been developed utilizing fuzzy memberships and thus producing a fuzzy classification rule.

3.2. Artificial neural network

Recently, there has been a great resurgence of research in neural network classifiers [28–32]. Artificial neural networks exhibit analogies to the ways that arrays of neurons function in biological learning and memory. The fundamental building blocks are units ('nodes') comparable to neurons, and weighted connections that can be likened to synapses in biological systems. The nodes are simple information processing elements, and their number and connection patterns can vary. The most widely used connection pattern is the three-layer backpropagation neural network [32] (Fig. 4), which has proved to be useful when modeling input–output relations [31–33] and is also used in this study. The number of nodes in the input and output layers coincide with the number of input and output variables in the data set whereas the ideal number of nodes in the hidden layer must be found experimentally. By varying the weights, between nodes, a network may be trained to reproduce the desired input–output relationship. The nonlinear transformation between input and output is

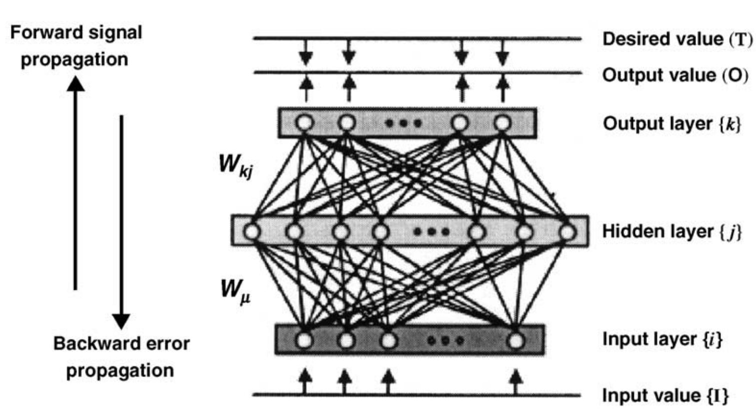

Fig. 4. Architectural layout of backpropagation neural networks.

performed by the neurons in the hidden layer, which transforms the weighted inputs using a transfer function (activation function) as shown in Fig. 5. The most commonly used transfer functions are the linear, log-sigmoid, and the tan-sigmoid functions [32]. Training consists of (i) calculating outputs from input data, (ii) comparing the measured and calculated outputs, and (iii) adjusting the weights for each node to decrease the difference between the measured and calculated values. This training procedure uses the back-propagation algorithm [32,33]. Long training to very low errors can result in over-training (or over-fitting), where a network gets worse instead of better after a certain point. Over-training makes the network memorize the example training patterns (including all of their peculiarities) to such an extent that it fails to generalize for new data. Care must be taken to see that training does not result in over-fitting.

3.3. Neuro-fuzzy classifier

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 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 has been incorporated into the neural network [40].

In general, there are two kinds of combinations between neural networks and fuzzy systems [40]. 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 pre-processor or as a post-processor 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 [40].

3.4. Projection neural network

The standard backpropagation training algorithm [32,33], while successful for problems of moderate size, suffers from slow training times, the potential to get stuck at local minima, and the need for a large number of hidden nodes when applied to complicated problems. However, in problems for which it does converge to a solution, it offers the advantage of ensuring error minimization. Therefore, when solving a classification problem, the network outputs will approach the Bayes conditional probabilities, given a statistically representative set of training data. On the other hand, there exist classification algorithms that train quickly but do not guarantee minimization of the classification error. Examples of these are the hypersphere classifiers, such as the restricted Coulomb energy network (RCE) [31], the models of adaptive resonance theory (ART) [28], and the Kohonen type networks [29]. In this study, we have used a projection network that combines the utility of both RCE [31] and backpropagation [33] approaches.

The classification algorithms that provide fast training do so by placing prototypes with closed decision boundaries around training data points and then adjusting their positions and/or sizes. As an example, a hypersphere classifier such as RCE places hyperspherical prototypes around training data points and adjusts their radii. Radial basis function networks can provide fast training as well as error minimization [30,34,35]. While several methods of determining the size, position and amplitude of the radial basis functions have

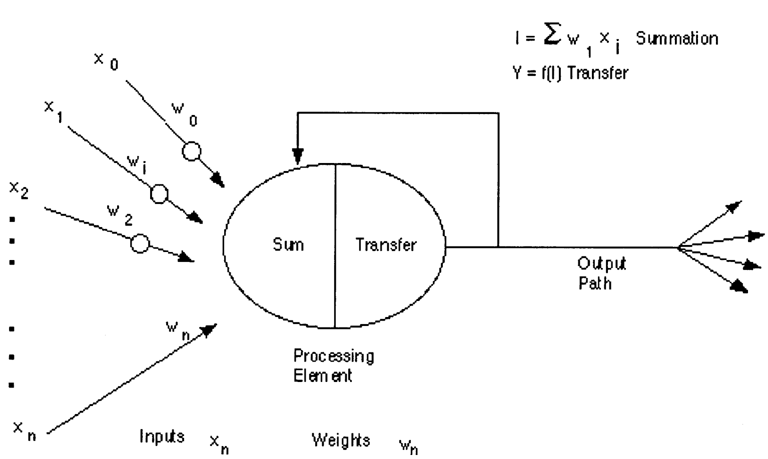

Fig. 5. Functional representation of single neuron.

been proposed they do not have the simplicity or computational efficiency of backpropagation training [36]. In contrast, the projection network [37] provides a means of implementing radial basis functions with a uniform approach to learning these parameters: backpropagation training of the weights and thresholds of a feedforward network [32]. This effectively leads to optimization of the prototypes' locations, size and amplitudes. Furthermore, both closed decision regions (hyperspheres or hyperellipses) and open ones (such as hyperplanes) are accommodated in the same network. Training of the network parameters may convert closed decisions regions to open ones and vice versa in the process of minimizing the error.

It is this ability to form closed prototypes with a single hidden node that allows the projection network to be initialized rapidly to a good starting point that is already close to a desirable error minimum. Any of a number of algorithms can be used for this initialization; Kohonen learning [29], RCE [31], and ART [28] are examples. Once the network has been initialized in this manner, modified backpropagation training is used to adjust the network weights and thresholds to ensure error minimization. Because the network begins near a good solution, one avoids the long training time which standard backpropagation would take to reach this point as well as the possibility of being stuck in local minima that might prevent one from reaching this point. The extension of a standard neural network to produce the projection network is a very simple one.

The neural network inputs are projected onto a hypersphere in one higher dimension and the input and weight vectors are confined to lie on this hypersphere. A single hidden level node is now capable of forming either an open or a closed region in the original input space. This basic concept is not new. The need to normalize the input vector and the weight vector so that their dot product is a measure of their closeness has been recognized for a long time [29]. Telfer and Casasent [38] have used a projection onto a cylindrical hyperbola for initialization of a network with no hidden layers. Saffrey and Thornton [39] have applied stereographic projection to the Upstart algorithm. By projecting the input vector onto a hypersphere in one higher dimension, one can create prototype nodes with closed or open classification surfaces all within the framework of a backpropagation trained feedforward neural network. In this way, one achieves rapid prototype formation through initialization and subsequent optimization through back-propagation training. Fig. 6 shows the typical structure of a projection network.

4. Classification of pipe defects

Given the potential advantages of neural networks over statistical methods for classification, the research purpose of this paper is to determine empirically how well these methods perform as classifiers for the classification of underground pipe objects. The statistical and neural classifiers are evaluated by comparing their performance on the classification of extracted feature vectors by the severity of distress present in the pipe images. The data set used for the evaluation of the classifiers is generated from previously segmented underground pipe images. The actual classification of each image is determined by human visual observation (Ontario Pipeline Inspectors). Two data sets are generated: one is used as a training data set, used to train each of the classifiers, and the other is used as a test data set, to evaluate the performance of each classifier on data not seen during training.

In this study, we propose to apply concepts to fuzzy logic to a projection neural network. We propose a homogeneous architecture, illustrated in Fig. 9, in which the fuzzy concepts appear simply in converting the input feature

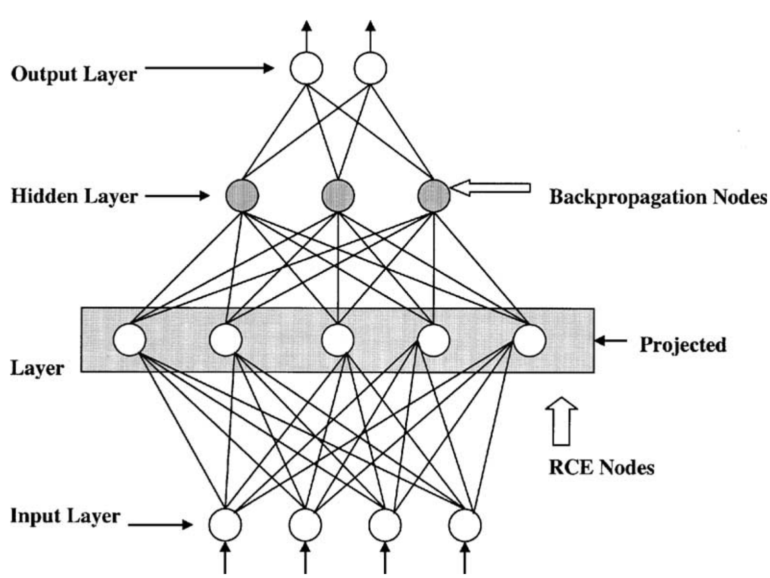

Fig. 6. The projection neural network architecture showing the combination of a reduced Coulomb energy (RCE) network and a backpropagation network.

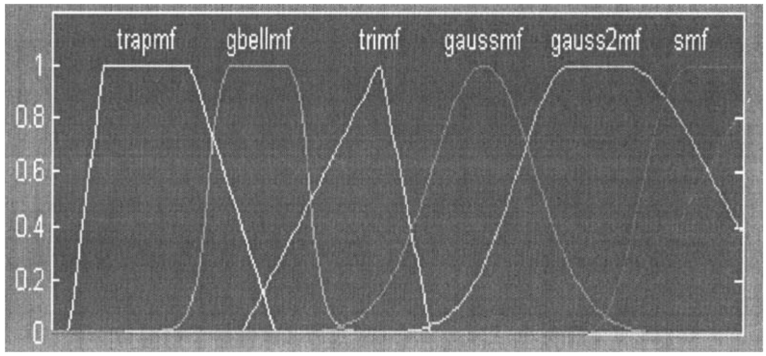

Fig. 7. Linguistic representation of various membership functions.

values into fuzzified data, which are input to the projection neural network. By providing comparatively simple, fuzzy features as inputs, the performance of the network is robustified, leading to superior classification results. The following sections detail the modified natures of inputs and outputs for the proposed network.

4.1. Proposed neuro-fuzzy projection network

In this study, we apply the fuzzy concept simply in converting feature values into fuzzified data, which are input and output to the projection neural network algorithm.

4.2. Input pattern representation in linguistic form

In the proposed neuro-fuzzy algorithm, we use the fuzzy data as inputs to neural network. Sometimes the variation of feature values is large, in which case it is difficult to classify objects correctly based on these feature values. To solve this problem, we first convert each object feature value into three fuzzy data [41], and then learning is performed with these fuzzy data using the projection network. Finally, we classify objects using the proposed neuro-fuzzy algorithm. There are several types of membership functions in representing fuzzy phenomena [24], as shown in Fig. 7. The proposed object classification algorithms are simulated using triangular, trapezoidal, and Gaussian membership functions. To convert normalized features into fuzzy data, we determine the MAX and MIN values that are the maximum and minimum feature values for entire data set, respectively. As shown in Fig. 8, we generate three membership functions denoted by 'S' (small), 'M' (medium), and 'L' (large). In the underground pipe object classification method using three membership functions (i.e., triangular, trapezoidal, and Gaussian), the extracted features are represented by means of linguistic variables specified by these membership functions.

4.3. Output class representation in linguistic form

In general, a 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 the network may be assigned with a nonzero membership instead of choosing the single node with the highest activation. It allows the modeling of fuzzy data when the feature space involves overlapping pattern classes, such that a pattern 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 a fuzzy network is equivalent to the conventional network.

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

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

The weight $1/\mu_{kj}$ accounts for the variance of the classes so that a feature with higher variance has less significance in

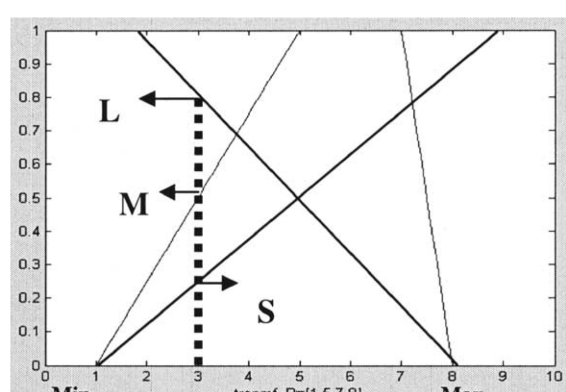

Fig. 8. Linguistic representation of feature values by trapezoidal membership function.

characterizing a class. The membership of the ith pattern to class C_k is defined as follows:

$$\mu_k(F_i) = \left(\frac{Z_{ik} - \min_k(Z_{ik})}{\max_k(Z_{ik}) - \min_k(Z_{ik})} \right) \text{ for } k = 1,\ldots,m. \quad (2)$$

Obviously $\mu_k(F_i)$ lies in the interval [0,1]. Except for the fuzzy membership desired values in the output layer, the training method and network structure is equivalent to the conventional neural network classifier.

4.4. Fuzzy input and output module and neural network module

The organization of the proposed fuzzy input and output modules and neural network is illustrated in Fig. 9. The neural network module is a conventional feedforward artificial neural network; a simple projection network is used in this study. As usual, the number of nodes in the input and output layers equals the number of input and output variables, and the number of nodes in the hidden layer is found experimentally. A log-sigmoid transfer function [31] is used for the hidden layer neurons, and a tan-sigmoid function is used for the output neuron. To increase the rate of training convergence, a momentum term and a modified backpropagation training [34] rule are used. The input layer of this network consists of $3I$ nodes (because of the use of fuzzy sets to screen the I input feature variables), and the output layer consists of C nodes (trained with C fuzzy output class values).

5. Performance comparison with other classifiers

To study the performance of the proposed neuro-fuzzy classifier and to compare its performance with that of other statistical and neural classifiers, we have used K-NN [23], fuzzy K-NN [42], and conventional backpropagation net-

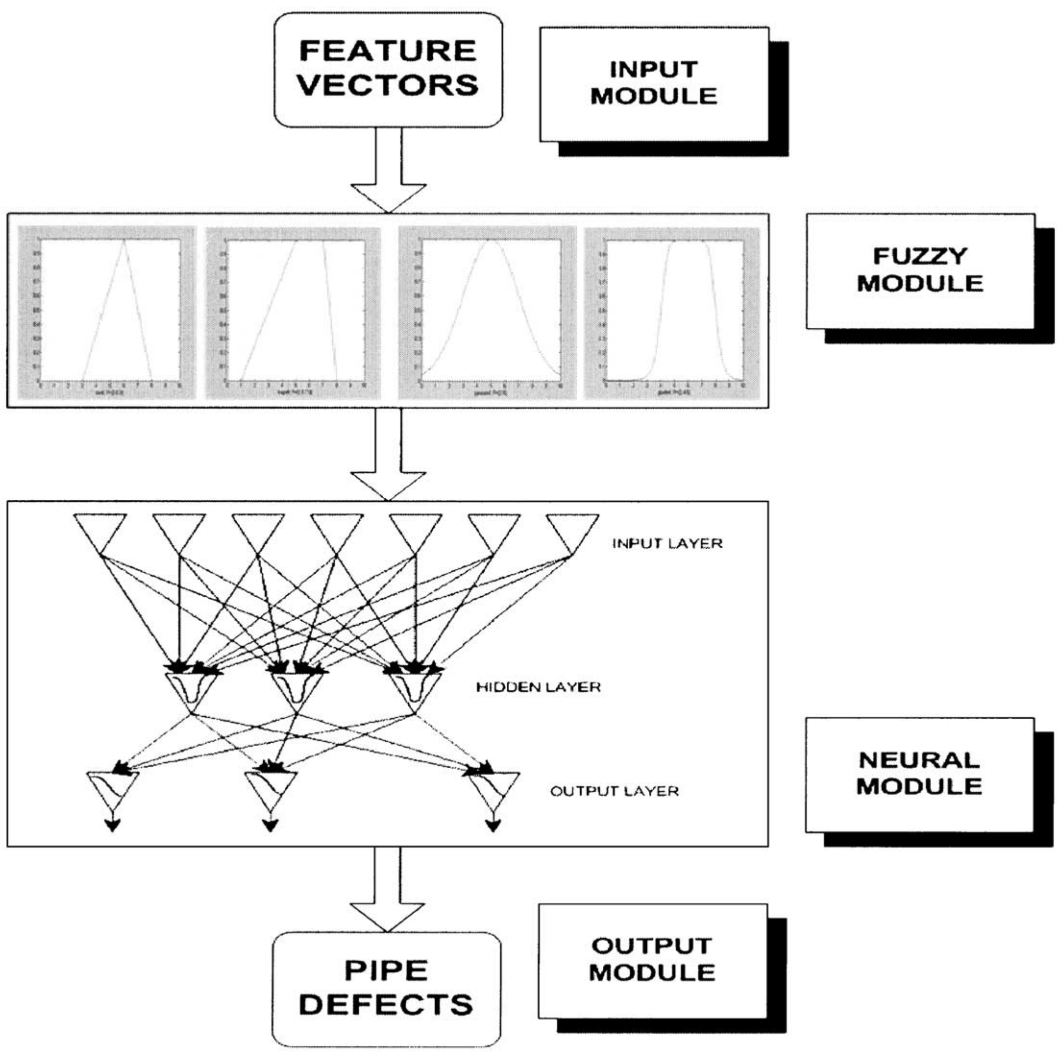

Fig. 9. The neuro-fuzzy neural network architecture with fuzzy inputs.

work classifiers. The theoretical background and relative advantages of these classifiers are discussed below.

5.1. The K-NN algorithm

Many classification methods assume that the form of class-condition densities is known. The popular maximum likelihood estimation [2] approach assumes multivariate normality. The K-nearest neighbor (K-NN) [23] procedure is a nonparametric classification procedure. This rule classifies a new feature vector y by assigning it the label most frequently represented among the K-nearest of all training samples [23]. The decision is made by determining the majority class represented in the set of K-nearest neighbors of a pattern by examining the labels of each of the K neighbors. Randomization is used for breaking ties. In practice, one chooses $K = c\sqrt{n}$ where c is an appropriate constant and n is the size of the training set. In the present study, c=1 is used.

5.2. The fuzzy K-NN algorithm

The fuzzy K-NN algorithm is considered one of the most accurate algorithms in pattern recognition [42]. 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 [2]. 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 memberships [42].

If $W=\{x_1,x_2,\ldots,x_n\}$ is the set of n labeled samples and u_{ij} is the membership of the jth labeled data in the ith class, then the fuzzy K-NN algorithm is described as follows [42].

Begin
Input y, of unknown classification.
Set K, $1\leq K\leq n$, Initialize i= 1
Do Until (K-nearest neighbours found)
Compute distance from y to x_i, If ($i\leq K$) Then
Include x_i in the set of K-nearest neighbors
Else if (x_i is closer to y than any previous nearest neighbour) Then
Delete farthest in the set of K-nearest neighbours
Include x_i in the set of K-nearest neighbours
End If, Increment i
End Do Until, Initialize i= 1
Do Until (y assigned membership in all classes)

$$\text{Compute } u_i(y) = \frac{\sum_{j=1}^{K} u_{ij}\left(\frac{1}{\|y-x_j\|^{\frac{2}{(m-1)}}}\right)}{\sum_{j=1}^{K}\left(\frac{1}{\|y-x_j\|^{\frac{2}{(m-1)}}}\right)} \tag{3}$$

Increment I, End Do Until, End

As shown in Eq. (3), the assigned memberships of observations are influenced by the class memberships of the K-nearest neighbours. The memberships of the labeled sample can be assigned in several ways such as using fuzzy cluster analysis or based on expert opinions. The distance between observations can be represented by any distance measure such as the Euclidean distance, defined as [25]

$$d_{yx_i} = \sum_{v=1}^{p}(y_v - x_{iv})^2 = (y-x_i)'(y-x_i) \tag{4}$$

where p=number of variables for observation i. With this distance, the variables are given equal weights. The variable m in Eq. (3) defines how heavily the distance is weighted when calculating each neighbor's contribution to the membership value [25].

5.3. The conventional backpropagation network

Several neural network models can be used in pattern classification (both supervised and unsupervised). For supervised pattern classification, the most commonly used ANN is the feedforward network trained using the back-propagation algorithm [32], which is adopted in the present study. The backpropagation algorithm can be described in three equations. First, weight connections are changed in

Table 1
Confusion matrix for the proposed neuro-fuzzy projection network classifier using a Gaussian membership function for classification of crack/hole defects

Class		Transverse crack	Longitudinal crack	Diagonal crack	Multiple crack	Mushroom crack	Minor holes	Major holes	Total
		1	2	3	4	5	6	7	
Transverse crack	1	43	0	2	0	0	0	0	45
Longitudinal crack	2	0	33	1	1	0	0	0	35
Diagonal crack	3	1	1	18	0	0	0	0	20
Multiple crack	4	0	0	0	58	2	0	0	60
Mushroom crack	5	0	0	0	2	13	0	0	15
Minor holes	6	0	0	0	0	0	53	2	55
Major holes	7	0	0	0	0	0	3	22	25
Total									255

Table 2
Confusion matrix for the proposed neuro-fuzzy projection network using a Gaussian membership function for classification of clean pipe and lateral/joint defects

Class		Clean pipe	Perfect joint	Eroded joint	Misaligned joint	Perfect lateral	Eroded lateral	Collapsed pipe	Total
		1	2	3	4	5	6	7	
Clean pipe	1	110	0	0	0	0	0	0	110
Perfect joint	2	0	42	7	1	0	0	0	50
Eroded joint	3	0	3	11	1	0	0	0	15
Misaligned joint	4	0	1	6	18	0	0	0	25
Perfect lateral	5	0	0	0	0	27	3	0	30
Eroded lateral	6	0	0	0	0	2	8	0	10
Collapsed pipe	7	0	0	0	0	0	0	5	5
Total									245

each learning step (k) with

$$\Delta w_{ij(k)}^{[s]} = \eta(t)\delta_{pj}^{[s]}x_j^{[s-1]} + m\Delta w_{ij(k-1)}^{[s]} \tag{5}$$

Second, for output nodes it holds that

$$\delta_{pj}^{[o]} = (d_j - o_j)f_j'\left(I_j^{[s]}\right) \tag{6}$$

and third, for the remaining nodes it holds that

$$\delta_{pj}^{[s]} = f_j'\left(I_j^{[s]}\right)\sum_k \delta_{pk}^{[s+1]}w_{jk}^{[s+1]} \tag{7}$$

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 (foe output nodes only). Parameter values (i.e., the learning rate $\eta(t)$, momentum factor m, and the number of hidden nodes h_j) are selected experimentally to be those that gave the best classification accuracy. The input and output nodes are selected according to the feature vectors and class of objects to be classified.

6. Experimental results and evaluation

We have applied the proposed approaches to 500 underground concrete sewer pipe images. These images are obtained from SSET inspection of flush cleaned concrete sewer pipes, 18 in. in diameter, from various municipalities in North America. In this study, 60% of the images are used for training the classifiers and the remaining 40% are used to test the classifiers. The training set of 60% images is randomly selected from each class of defects in the 500 image database. To allow for comparison between the five classification methods, results are presented to show the difference in the magnitude of classification accuracy compared to expert classification (further details can be found in the doctoral thesis research [43]). The overall classification accuracy for the proposed neuro-fuzzy algorithm with Gaussian membership function is calculated by constructing a confusion matrix between the experts' decisions and classifier results, as shown in Tables 1 and 2.

In Table 3, we show the overall classification results of the fuzzy approach with different membership functions. We can observe that the fuzzy network based on Gaussian membership functions has better classification rates; therefore we have selected this network as the basis of comparison with the other classifiers.

Table 4 compares the classification rates for the five classification methods. In general, the three neural network approaches performed better and produced more consistent results than the K-NN and fuzzy K-NN classifiers. It is clear, however, that the overall performance of the proposed neuro-fuzzy model is better than that of the other classifiers. Although there is only a slight improvement in classification rate between the projection and backpropagation networks, the projection network learned much faster and required fewer nodes in the hidden layer.

One of the most important attributes of the neural classifiers, in general, is their ability to spot patterns in data that classical pattern recognition systems may not be able to

Table 3
Classification accuracy by proposed neuro-fuzzy projection network

Classifier	Fuzzy input	Membership function	Fuzzy output	Classification accuracy (%)		
				Crack/hole	Joint	Lateral
1	Yes	Triangular	No	91	83.2	87.1
2			Yes	91.7	84.5	87.3
3		Trapezoidal	No	92.3	86.2	88.2
4			Yes	93.2	87.5	88.7
5		Gaussian	No	92.9	87.7	89.9
6			Yes	94.1	88.2	91.8
7	No	No	Yes	90.3	82.8	86.8

Table 4
Comparison of the performance evaluation of the proposed neuro-fuzzy projection network classifier with that of four other classifiers

Classifier	Classification methods	Classification accuracy (%)		
		Crack/hole	Joint	Lateral
1	K-NN	81	76.8	80.3
2	Fuzzy K-NN	84.6	79.3	82.9
3	Backpropagation network	87.2	81.6	84.5
4	Projection network	89.5	82.1	86
5	Neuro-fuzzy projection network	94.1	88.2	91.8

detect. Therefore, we see the proposed neuro-fuzzy projection classifier as an excellent tool for dealing with environments that are highly unstructured and that may involve incomplete or noisy data (such as underground pipe images).

7. Conclusions

In this paper, we proposed a neuro-fuzzy classifier that combines neural networks and fuzzy concepts for the classification of objects in segmented underground pipe images. 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 different features of the object present in the segmented image based on the geometric shape and size. These features values are then fuzzified and applied to the neuro-fuzzy network in the classification step. We have shown simulation results of the proposed neuro-fuzzy algorithm in comparison to the K-NN method, fuzzy K-NN method, and conventional backpropagation algorithm. Simulation results show that the proposed neuro-fuzzy algorithm using a combination of Gaussian membership functions and projection neural networks gives better classification results than the other statistical and neural network methods. The results show the promise of the proposed fuzzy-neural network as a tool for classifying objects in the segmented underground pipe images based on extracted feature vectors.

References

[1] P. Dodwell, Visual Pattern Recognition, Holt, Rinehart, and Winston, New York, 1970.

[2] R.O. Duda, P.E. Hart, Pattern Classification and Scene Analysis, Wiley Publication, New York, 1970, pp. 271–272.

[3] R. Gnanadesikan, Methods for Statistical Data Analysis of Multivariate Observations, Wiley, New York, 1977.

[4] E. Hunt, Artificial Intelligence, Academic Press, New York, 1975.

[5] A. Reynolds, P. Flagg, Cognitive Psychology, Winthrop, MA, 1977.

[6] K.T. Spoehr, S.W. Lehmkuhle, Visual Information Processing, Freeman, San Francisco, CA, 1982.

[7] P. Winston, Artificial Intelligence, Addison-Wesley, Reading, MA, 1977.

[8] A. Wardle, L. Wardle, Computer aided diagnosis, Methods Inf. Med. 17 (1) (1978) 15–28.

[9] R.J. Schalkoff, Pattern Recognition: Statistical, Structural, and Neural Approaches, John Wiley and Sons, Inc., New York, NY, 1992.

[10] K. Mehrotra, C.K. Mohan, S. Ranka, Elements of Artificial Neural Networks, MIT Press, Cambridge, MA, 1997.

[11] S.K. Sinha, F. Karray, Classification of underground pipe scanned images using feature extraction and neuro-fuzzy algorithms, IEEE Trans. Neural Netw. 13 (2) (2002) 393–401.

[12] O. Moselhi, T. Shehab-Eldden, Automated detection of defects in underground sewer and water pipes, Autom. Constr. 8 (5) (1999) 581–588.

[13] O. Moselhi, T. Shehab-Eldden, Classification of defects in sewer pipes using neural networks, J. Infrastruct. Syst. 6 (3) (2000) 97–104.

[14] M.J. Chae, D.M. Abraham, Neuro-fuzzy approaches for sanitary sewer pipeline condition assessment, J. Comput. Civ. Eng. 15 (1) (2001) 4–14.

[15] H.D. Cheng, Automated real-time pavement distress detection using fuzzy logic and neural networks, SPIE Proc. Nondestr. Eval. Bridges Highw. (1996) 140–151.

[16] M.S. Kaseko, S.G. Ritchie, A neural network based methodology for pavement crack detection and classification, Transp. Res., vol. 1 (4), Transportation Research Board, Washington, DC, 1993, pp. 275–291.

[17] S.K. Sinha, P.W. Fieguth, 'Segmentation of buried concrete pipe images,' Automation in Construction (in press).

[18] S.K. Sinha, P.W. Fieguth, 'Automated detection of cracks in buried concrete pipe images,' Automation in Construction (in press).

[19] M.A. Shaikh, B. Tian, Neural network based cloud detection/classification using textural and spectral features, Proc. of IGRASS, Lincoln, NB, 1996, pp. 1105–1107.

[20] R.L. Bankert, Cloud classification of AVHRR imagery in maritime using a probabilistic neural network, J. Appl. Meterol. 33 (1994) 909–918.

[21] R.M. Haralick, Textural features for image classification, IEEE Trans. Syst. Man Cybern. 3 (1973) 610–621.

[22] A.K. Jain, Fundamentals of Digital Image Processing, Englewood Cliffs, New Jersey, 1989.

[23] T.M. Cover, P.E. Hart, Nearest neighbor pattern classification, IEEE Trans. Inf. Theory 13 (1967) 21–27.

[24] L.A. Zadeh, Fuzzy sets, Inf. Control 8 (1965) 338–353.

[25] J.C. Bezdek, Pattern Recognition with Fuzzy Objective Function Algorithms, Plenum Press, New York, 1981.

[26] M. Gupta, R. Ragade, P. Yager, Advances in Fuzzy Set Theory and Applications, North Holland, Amsterdam, 1979.

[27] A. Kandel, Fuzzy Techniques in Pattern Recognition, John Wiley, New York, 1982.

[28] G.A. Carpenter, S. Grossberg, A massively parallel architecture for a self organizing neural pattern recognition machine, Comput. Vis. Graph. Image Process. 37 (1987) 54–115.

[29] T. Kohonen, Self Organizing Maps, Springer Verlag, New York, 1995.

[30] M.J.D. Powell, Radial Basis Functions for Multivariable Interpolation: A Review, Clarendon Press, Oxford, 1987.

[31] D.L. Reilly, L.N. Cooper, C. Elbaum, A neural model for category learning, Biol. Cybern. 45 (1982) 35–41.

[32] D.E. Rumelhart, J. McClelland, Parallel Distributed Processing, vol. 1, MIT Press, Cambridge, MA, 1986.

[33] P. Werbos, Beyond regression: new tools for prediction and analysis in the behavioral sciences, PhD dissertation, Harvard (1974).

[34] J. Moody, C. Darken, Fast learning in networks of locally tuned processing units, Neural Comput. 1 (2) (1989) 281–294.

[35] T. Poggio, F. Girosi, Networks for approximation and learning, Proc. of the IEEE Neural Networks Conf., vol. 78 (9), 1990, pp. 1481–1497.

[36] F.J. Pineda, Recurrent backpropagation and the dynamical approach to adaptive neural computation, Neural Comput. 1 (1) (1989) 161–172.

[37] G. Wilensky, N. ManuKian, The projection neural network, Proc. of the Intl. Joint Conf. on Neural Networks, vol. 2, 1992, pp. 358–367.

[38] B. Telfer, D. Casasent, Minimum cost Ho–Kashyap associative processor for piecewise hyperspherical classification, Proc. of the Intl. Joint Conf. on Neural Networks, vol. 2, 1991, pp. 89–94.

[39] J. Saffery, C. Thornton, Using stereographic projection as a preposessing technique for upstart, Proc. of the Intl. Joint Conf. on Neural Networks, vol. 2, 1991, pp. 441–446.

[40] C.T. Lin, C.S.G. Lee, Neuro-Fuzzy Systems, Prentice-Hall, New Jersey, 1996.

[41] S.K. Pal, S. Mitra, Multilayer perceptron, fuzzy sets, and classification, IEEE Trans. Neural Netw. 3 (5) (1992) 683–696.

[42] J.M. Keller, M.R. Gray, J.A. Givens, A fuzzy K-nearest neighbor algorithm, IEEE Trans. Syst. Man Cybern. 15 (1985) 580–585.

[43] S.K. Sinha, Automated Underground Pipe Inspection Using a Unified Image Processing and Artificial Intelligence Methodology, PhD thesis, University of Waterloo, 2000.