Development of an Intelligent System for Automated Pavement Evaluation

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A potential automated pavement evaluation system to address multisensor applications; integrate different types of sensors, techniques, and information; and offer more sophisticated and intelligent processing capabilities for improved pavement management is described. The separate components of this system either now exist in prototype form or are under development. Such a system could automate in real time much of the pavement data acquisition, interpretation, and evaluation process, and capture the experience and judgment of expert pavement engineers in performing condition assessments and identification of appropriate rehabilitation and maintenance strategies. This research is directed toward an innovative, noncontact, intelligent nondestructive evaluation (INDE) system, using a novel artificial intelligence (AI)–based approach that would integrate three AI technologies: computer vision, neural networks, and knowledge-based expert systems, in addition to conventional algorithmic and modeling techniques. The focus of the current, initial research is development of an advanced sensor processing capability using neural network technology to determine the type, severity, and extent of distresses from digitized video image representations of the pavement surface acquired in real time. The properties of neural networks provide potential solutions to the inherently difficult nature of sensor integration and output interpretation in automated pavement evaluation. The background and conceptual development of an INDE system for automated pavement evaluation, and initial research results that demonstrate the feasibility of a neural network approach in a case study application using a multilayer perceptron and a backpropagation learning rule, are described.

The vast public works infrastructure in the United States includes highway, bridge, mass transit, aviation, port, harbor, water supply, wastewater, solid waste, power supply, school, hospital, and other facilities. The deterioration of this infrastructure and the implications for public safety and continued provision of essential services have become major issues in recent years.

The development of economical and reliable nondestructive evaluation (NDE) techniques holds great promise for assessing the physical and operational condition of such large structural systems, and their component construction materials, to quantitatively evaluate the adequacy, remaining life, and safety of a structure. Implementation of NDE techniques involves three major steps: (a) placement of sensors at strategic positions on the structure, (b) recording and processing of the measurements from the sensors, and (c) interpretation and evaluation of the results.

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A variety of sensors can be used in nondestructive testing of civil engineering structures. The type to be used and where they are placed on the structure depend on the kind of measurements desired and the type of structure. The sensors may be of one or more technologies using mechanical, electrical, acoustic, nuclear, radar, and optical techniques.

In order to evaluate the condition of a structure or structural component, the sensor measurements have to be processed and analyzed. The analysis may be based on established relationships (i.e., analytical models) between sensor measurements and structure characteristics or properties of interest; or may be based on a set of rules for interpretation of the results; or a combination of both approaches. The larger the volume of sensor data collected, the more difficult the processing is likely to be, as observed by several researchers (*1*). This observation is particularly so where noncontact optical scanning methods are used for surface distress detection on pavements, bridges, and other large civil engineering structures, where video or photographic images of the surfaces are acquired and need interpretation in real time or are processed later in the laboratory or office. In either case, the analysis involves processing the images and extracting relevant data for identification of the type, severity, and extent of distress on the structure.

Very often, no single NDE technique offers the capability to provide all the information required for evaluation of structures and structural components (*2,3*). Therefore, there is frequently a need to use and integrate various combinations of nondestructive testing techniques on a single structure or structural component to assess its structural performance, adequacy, or material properties. This need can result in a vast amount of data from various sensors that may not only pose problems in the processing stage, but may also cause difficulty in understanding and modeling the combined information. For example, in the case of highway pavements, different types of devices, sensors, and measurements can be used and combined to assess the pavement's surface distress, longitudinal profile, skid resistance, and structural adequacy, as part of the overall pavement evaluation process.

A potential automated pavement evaluation system to address multisensor applications, integrate different types of sensors, techniques, and information, and offer more sophisticated, intelligent processing capabilities for improved pavement management is described. The separate components of this system either now exist in prototype form or are under development. Such a system could automate in real time much of the pavement data acquisition, interpretation, and evaluation process, and capture the experience and judgment of expert pavement engineers in performing condition assessments and identification of appropriate rehabilitation and maintenance strategies.

The focus of this current, initial research is development of an advanced sensor processing capability using neural network technology to determine the type, severity, and extent of distresses from digitized video image representations of the pavement surface acquired in real time. The properties of neural networks provide potential solutions to the inherently difficult nature of sensor integration and output interpretation in automated pavement evaluation. The background and conceptual development of an INDE system for automated pavement evaluation, and initial research results that demonstrate the feasibility of a neural network approach in a case study application using a multilayer perceptron and a backpropagation learning rule, are described in the following sections.

BACKGROUND

The ultimate objective of the research is to develop an innovative, noncontact, intelligent NDE (INDE) system using a novel artificial intelligence (AI)–based approach integrating three AI techniques:

- Computer vision,
- Neural networks, and
- Knowledge-based expert systems (KBES),

in addition to conventional algorithmic and modeling techniques. Such an approach should be feasible and should have a high probability of success.

A simplified structure for this system in an application mode is shown in Figure 1. In this model, massive amounts of data from single, multiple, and different types of sensors (e.g., optical and electrical sensors for measuring pavement distress, roughness, skid resistance, and structural condition) can be

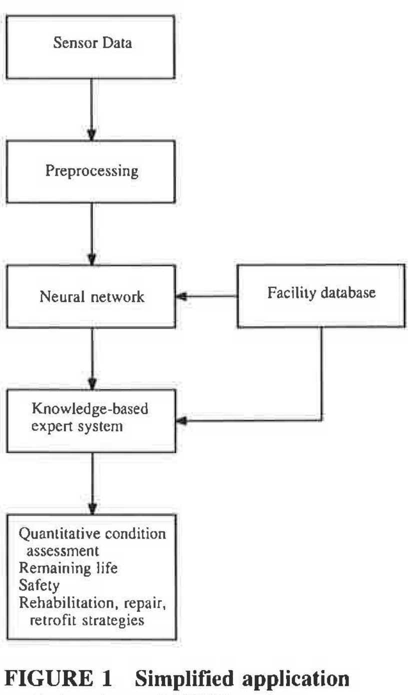

FIGURE 1 Simplified application and structure of INDE system.

integrated and processed by the neural network to quantitatively characterize the condition of the structure on the basis of the analysis of the pattern of the different sensor measurements. This data acquisition and processing phase could be accomplished in real time to save data storage and subsequent time requirements for postprocessing, thereby improving economy and productivity significantly. Application of neural networks is proposed for this stage because of the excellent pattern classification characteristics these models have shown in various applications in other areas (*4–6*).

The subsequent KBES evaluation of the structure would take as input from the neural network the type, extent, and severity of structural distresses as well as other pertinent characteristics, and would access historical records such as rates of deterioration, design details, climatic factors, etc., from a facility data base (such as that for a pavement management system). The KBES would apply symbolic reasoning on the basis of the experience and knowledge of expert engineers, combined with conventional algorithmic models to quantitatively determine the structural adequacy, remaining life, and safety of the structure, as well as identifying (where appropriate) feasible rehabilitation, repair, and retrofit strategies, including detailed designs.

In the initial development of this INDE system, its application to flexible highway pavements is under investigation. In this application, the sensor data are a series of digitized pavement images that have to be processed to determine the type, severity, and extent of surface distress existing on the pavement. A real time vision and imaging system is required for acquisition of the pavement images. Such systems already exist [e.g., the Pavement Distress Imager by Roadman-PCES, Inc. (*7*)] and should be an integral part of the INDE system. Another basic element of the system, a KBES pavement rehabilitation analysis and design system, already exists in prototype form. It has been developed at the University of California at Irvine (*8–11*).

The focus of the initial and current research is therefore a critical element of an INDE system, an advanced multisensor processing capability using neural network technology. A specific objective of this component of the INDE system is to determine the type, severity, and extent of distresses from digitized video image representations of the pavement surface. (Each pixel in the image essentially provides a sensor value so that in a common 512 × 512 pixel image there would be 262,144 sensor values to process.)

Typical indicators of structural and functional asphalt concrete pavement performance include the following types of distress:

- Alligator, fatigue, or wheel path cracking;
- Longitudinal cracking;
- Transverse cracking;
- Patching and potholes; and
- Block cracking.

In addition, the severity and extent of these distresses are required. For example, in the case of fatigue cracking, this might involve the percentage length of the wheelpaths cracked and whether the severity involves only hairline cracking or pumping and spalling. Similar measures of severity and extent are relevant for other distress types.

Currently, collection of surface condition data usually involves manual visual inspection of the pavement surface by field personnel throughout the whole pavement system. This method is often dangerous, labor-intensive, and tedious, and potentially involves a high degree of variability and systematic error among personnel and regions of a state, as well as between states. Nevertheless, these same data form the basis of annual investments in the United States of billions of dollars in pavement rehabilitation programs. Considerable interest therefore exists in developing an automated system to capture and extract pavement surface distress data from video images cost-effectively, for NDE of highway systems.

A fully automated system for pavement surface distress data collection would offer several advantages over the manual system. Such a system would improve safety and efficiency of the data collection exercise, and could offer consistency and uniformity of data and data quality, both locally and nationally. It could also facilitate distress data collection at higher sampling rates.

Success of the INDE approach in this application area would also be significant for NDE of other concrete structures such as bridges, tunnels, and building exteriors, as well as for development of INDE systems for other types of large structural systems, for which this prototype could serve as a basis.

DEVELOPMENT OF AN INDE SYSTEM

The following discussion of the INDE system is presented in the context of the development of an automated pavement evaluation system.

Digital Imaging Concepts

Current efforts to automate the visual rating of pavement surface condition focus on the application of computer vision and image processing technology. Most of the systems currently under development involve four main steps, namely, (a) acquisition of video images of the pavement at highway speeds, (b) conversion of the video images into digital images, (c) preprocessing of the digital images for noise removal and distress identification, and (d) classification and quantification of the distress (*12*).

Digital imaging concepts and applications in pavement management were recently discussed by Ritchie (*12*). Briefly, computer vision involves the use of sensors and computers to emulate human vision, and has been the research subject of computer scientists and electrical engineers for several decades. As applied to pavement management, the sensors used are usually optically based, as in a video camera. The objective is to develop an automated approach to collect and evaluate pictorial data of the pavement surface.

A digitized image is essentially a mathematical representation of a normal pictorial image (in color or gray tones). Each digitized frame consists of an array of integer-valued picture-elements, or pixels. A common array size is 512 × 512 pixels, i.e, 512 lines vertically and 512 elements horizontally. The integer value of each pixel represents the color or gray tone of the corresponding area in the original. In pavement imaging work, 8 bits per pixel are common, permitting 2^8 or 256 gray tones (0 is black, 255 is white). In this case, each pixel requires 1 byte, resulting in 262,144 bytes of storage per frame.

With proper illumination, pavement cracks can be observed on the basis of the shadow associated with the pavement separation (*13*). Cracked regions in an image therefore typically have low pixel values, because the crack shadows are much darker than the surrounding pavement. These differences in gray scale values can be detected and the cracked areas isolated, for example, by threshold techniques. The number of pixels indicating cracking can be counted and the proportion of the area cracked can be determined.

Figure 2 shows some of these ideas in a histogram of pavement gray scale pixel values for a 32 × 32 pixel section or "tile," representing 1.5 × 3 in. of an actual pavement surface containing distress. By setting all pixel values equal to about 60 or more (in this case) to white, and all those under 60 to black, the modified image will, predominantly, indicate the cracked area, as represented by the black pixels. Before performing this binary thresholding, the image could be cleaned up and noise removed using other suitable image processing algorithms.

Recent developments in the application of digital imaging technology to automate the visual rating of pavement surface condition were presented at the First International Conference on Applications of Advanced Technologies in Transportation Engineering, held in San Diego, California, in 1989.

Several of the most noteworthy systems, from the United States, Japan, and France, included the Roadman-PCES system (*7*), the Komatsu system (*14*), and the MACADAM system (*15,16*), respectively. The Roadman-PCES system is providing the digitized images for use in this research. This system comprises a mobile unit, called the Pavement Distress Imager-1 (PDI-1) that uses controlled lighting and four line-scan cameras to collect 8-ft-wide continuous pavement surface images at speeds up to 68 mph. Pixel size is 0.1 in. longitudinally and

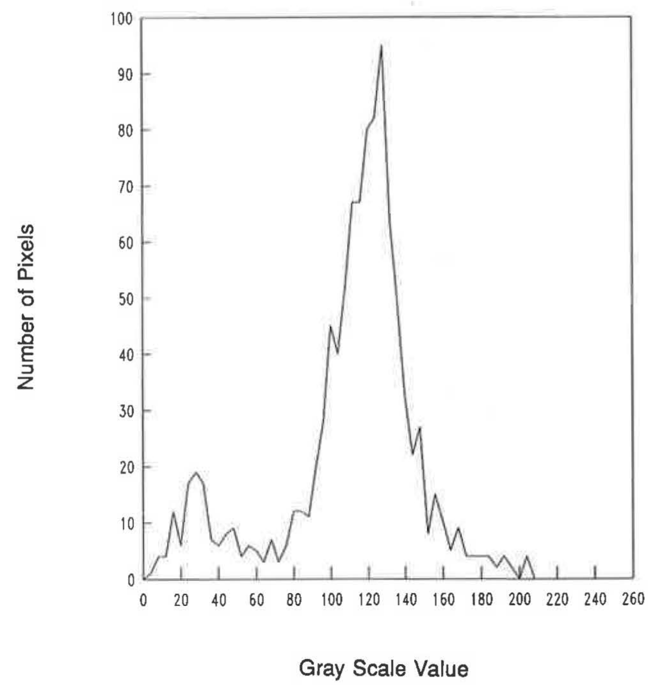

FIGURE 2 Histogram of gray scale values.

0.05 in. laterally. Postprocessing derives measures of pseudocracking with classifications of transverse, longitudinal, and other cracking. The Komatsu system comprises a survey vehicle and data processing system to simultaneously measure cracking, rutting, and longitudinal profile. A massive 64 (eventually up to 512) MC68020 parallel microprocessors are used to postprocess the crack image data using conventional image processing techniques. Even so, the system still does not apparently output the type, severity, and extent of cracking. The MACADAM system also uses conventional image processing methods to postprocess digitized continuous 35-mm films of pavement surface condition. Although the system aims to identify distress types, it appears to suffer from two limitations. The pixel size is almost 9 mm, which would provide very coarse resolution, severely limiting the size of cracks that could be detected. Also, the system is slow, processing about 1 km of pavement per hour.

The limited success to date of conventional image processing techniques in identifying the type, severity, and extent of distress in asphalt concrete pavement surfaces led to interest in an alternative approach, involving neural networks. This approach offers many advantages, including faster processing times because of the characteristic parallel processing approach these models use, their ability to tolerate noise in input data, and others, as discussed in the next section. The initial exploratory results (reported later) are most promising, supporting the high potential of the technique for this class of pattern recognition problem.

Neural Network Concepts

Research and development in neural networks has been accumulating since the early 1960s. Neural networks are information processing structures that are based on simplified theoretical models of the functioning of the human brain, in which brain cells (neurons), and their interconnections, can quickly perform complex calculations. These networks consist of many simple processing elements (neurons) that have densely parallel interconnections. A single neuron can receive weighted inputs from many other neurons, and can communicate its outputs, if any, to many other neurons. Information is thus represented in a distributed fashion, across the weighted interconnections. Such networks have exhibited learning, memory, an ability to handle noisy real-world data, and other significant capabilities. Neural networks can be implemented in hardware as parallel computing devices or as software simulations run on conventional serial computers. One of the principal applications of neural networks is to pattern recognition problems.

A neural network is defined by the topology of the network, the characteristic or transfer function of each processing element, and the learning or adaptation rule used to modify the connection weights between processing elements. Some of the important properties of neural networks include self-organization and generalization from training set input-output data, graceful degradation caused by parallel distributed processing nature of the network, and fuzzy decision-making capability.

These properties have the potential to provide solutions to the inherently difficult nature of the problem of sensor integration and output interpretation. The neural network model that is explored in this research is the multilayer perceptron.

Knowledge-Based Expert System Concepts

In the 1970s, research led to domain-dependent computer programs that were expert in specific professional domains. Such expert or knowledge-based systems are designed to emulate the performance of an expert, or group of experts, in a particular problem area, largely through the use of symbolic reasoning. These systems are therefore applicable to problems requiring specialized knowledge, skill, experience, or judgment for determination of solution strategies and solutions. Such problems have been ill structured in the sense that a numerical algorithmic solution is not available or is impractical.

Ongoing research at the University of California at Irvine (*9*) has resulted in the development of a microcomputer-based, integrated set of interacting expert systems and algorithmic models known as Pavement Rehabilitation Analysis and Design Mentor (PARADIGM). PARADIGM is largely driven by surface distress data of the sort that is expected to generate automatically and reliably with a neural network approach as part of the INDE system. Currently, data input to PARADIGM is interactive by a user. However, the system could readily accept these data from a neural network in conjunction with a pavement management system data base, in an automated fashion. This ability is a logical and highly desirable step to achieve greater productivity, reliability, and economy, while still allowing a user to benefit from the expert system's explanatory and tutorial capabilities. This natural linkage to PARADIGM provides a powerful contribution to the development of an INDE system. A brief description of the existing PARADIGM prototype follows.

PARADIGM consists of three main component systems: SCEPTRE, OVERDRIVE, and Network Optimization. These three main systems are represented and controlled through the production rules in the knowledge base of PARADIGM. The overall structure of PARADIGM is shown in Figure 3.

SCEPTRE evaluates project-level pavement surface distress and other user inputs and recommends feasible rehabilitation strategies for subsequent detailed analysis, design, and network optimization. SCEPTRE also performs cost-effectiveness analysis, on the basis of life cycle costs and pavement performance, for each feasible strategy. Surface condition evaluation is typically based on interpretation of field measurements relating to three performance indicators: ride quality, safety, and surface distress. Evaluation of a pave-

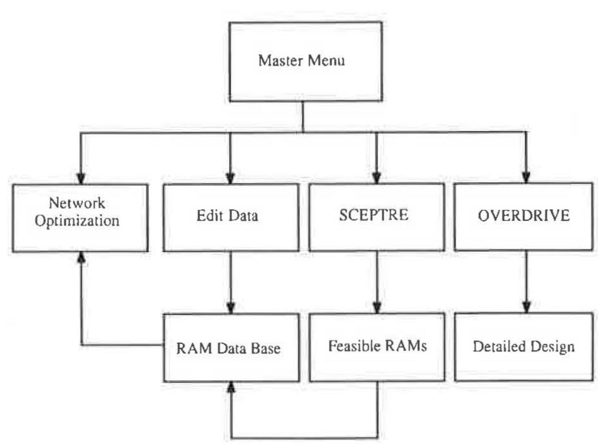

FIGURE 3 Overview of PARADIGM structure.

ment's surface condition enables a judgment to be made regarding the pavement's adequacy for current service and probable causes of surface distress, as well as the need for structural evaluation. It is also used to determine the need and priority for various maintenance and rehabilitation strategies, on the basis of expert judgment. Of the three performance indicators used in the pavement surface condition evaluation, the most important is surface distress.

The knowledge base in SCEPTRE has been constructed using the combined expertise of two pavement specialists with extensive experience in pavement rehabilitation in the states of Washington and Texas in the United States. The specific types of surface distress in SCEPTRE are compatible with those used in the Washington State Department of Transportation's (WSDOT's) pavement management system (PMS).

OVERDRIVE is an expert system for the assessment of existing structural adequacy, and the design of flexible asphalt concrete overlays on existing flexible pavement. OVERDRIVE is based on the component analysis overlay method, which is a traditional design method that involves a comparison between the existing pavement structure in terms of its component layers and a new full-depth design, and takes into account site-specific conditions such as the severity and extent of distresses, number of pavement layers and their thicknesses and materials, and subgrade strength and traffic loading. Evaluation of the existing pavement structure focuses on determining the effective thickness of each layer of the pavement. OVERDRIVE can also perform life cycle cost analysis of both the overlay and do nothing alternative through an interface to an external program.

The knowledge base of OVERDRIVE is the result of knowledge engineering efforts with a pavement specialist combined with a synthesis of state-of-the-art and other reports, papers, and manuals relating to the Asphalt Institute overlay design method for asphalt concrete overlays on flexible pavement.

Case study applications of PARADIGM have been performed using, in part, actual field data provided by WSDOT. SCEPTRE has been successful in identifying the feasible RAMs and most cost-effective RAM strategy compared with the actual decisions of WSDOT. Although there are variations between the major overlay design methods, the comparative performance of OVERDRIVE has been found to be most encouraging. OVERDRIVE continues to be used on a regular basis in practice by WSDOT.

THE MULTILAYER PERCEPTRON

The multilayer perceptron (MLP) is probably the most studied neural network model, although no applications to date of it or other neural network models in civil engineering are known. The MLP consists of three or more layers of neurons, or processing elements, with each neuron in a layer connected to all neurons in the preceding or following layers of neurons, or both, through weighted interconnections. This topology represents the evolution of the previous two-layer network introduced by Rosenblatt (*17*). The output of each neuron in a layer is a function of the sum of the weighted outputs of all the neurons in the immediate preceding layer. When the MLP is used as a pattern classifier, a vector to be classified is presented in the input layer and the computed vector at the output layer corresponds to the classification of the input pattern. The MLP can generate any set of hyperplanes in the information vector space to separate classes, making it suitable for pattern classification work, which is the primary reason for selecting it for this application.

Design and implementation of an MLP requires two phases, a training phase and a testing phase. In the training phase, a backpropagation learning algorithm (*5,6*) is used to adjust the weights between each pair of interconnected neurons using a set of training images. The training is done by presenting the MLP with a set of training patterns and adjusting iteratively the connection weights as a function of the error between the computed output and desired output for each input pattern. The next phase is to test the trained MLP (i.e., the generated weight matrix) with a second set of images to evaluate how accurately it is able to correctly classify the input patterns.

As compared to other neural network paradigms such as the bidirectional associative memories (BAM) and the Hopfield crossbar network, the three-layer perceptron is simpler to implement and has better performance in capacity and percentage of correct recall.

For the INDE system, the use of a three-layer perceptron, whose schematic representation is shown in Figure 4, is under investigation. The network shown has P processing elements (PEs) in the input layer, Q PEs in the output layer, and a variable number of PEs in the middle or hidden layer. The characteristic equation is identical for all PEs. For the nth PE in the mth layer, the output is defined by

$$o_{m,n}(t + 1) = f\left[\sum_{k=1}^{N_{m-1}} o_{m-1,k}(t)W_{m-1,k,n}(t) - \theta_{m,n}\right] \tag{1}$$

where

t = discrete time index,
m = 2 for the hidden layer PEs and 3 for the output layer PEs,
N_{m-1} = number of PEs in layer $m - 1$,
$W_{m-1,k,n}$ = weight of the interconnection between $PE_{m-1,k}$ and $PE_{m,n}$,
$\theta_{m,n}$ = threshold for $PE_{m,n}$, and
f = nonlinear activation function.

This function is typically selected as a monotonically increasing bounded function. A sigmoid function is usually used.

The learning law for the perceptron is a simple error feedback. The network learns the associations between input and output patterns by being exposed to many training samples. The samples are presented to the perceptron repeatedly and each time the weight matrix is adjusted in proportion to the

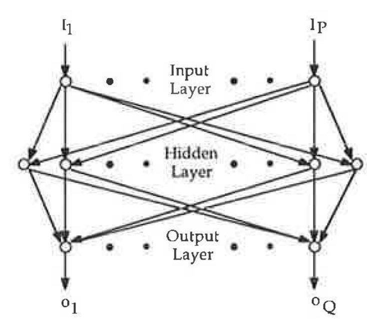

FIGURE 4 ***P*** **input–*Q*** **output three-layer perceptron.**

error between the computed and the desired outputs until the desired target output is produced. This weight adaptation strategy is referred to as the backpropagation learning law. At the output layer, the error associated with $PE_{3,j}$ is

$$e_{3,j} = d_j - o_{3,j} \tag{2}$$

where d_j is the desired output of the jth output PE and $o_{3,j}$ is its actual output. The error for the ith PE in the hidden layer is defined as

$$e_{2,i} = \sum_j e_{3,j} W_{2,i,j} \tag{3}$$

The weight adaptation law is then given by

$$W_{m-1,i,j}(t + 1) = W_{m-1,i,j}(t) + \Delta W_{m-1,i,j}(t + 1) \tag{4}$$

where

$$\Delta W_{m-1,i,j}(t + 1) = \eta e_{m,j} o_{m-1,i} f' \left[\sum_{k=1}^{N_{m-1}} o_{m-1,k}(t) W_{m-1,k,j}(t) - \theta_{m,j} \right] \tag{5}$$

and f' is the derivative with respect to the function argument, and η is a parameter of the learning rate and is always $0 < \eta < 1$. Rumelhart et al. (*5*) found that for a sigmoid function the adaptation law is an implementation of the gradient descent in the output error. Although the gradient descent procedure does not provide any theoretical proof that a solution can be found, Rumelhart et al. (*5*) and other researchers have tested the procedure in a number of practical problems and have found that it led to solutions in most cases. The potential problem of local minima was rarely encountered. Hence, convergence of the learning process using backpropagation can be achieved in most practical applications.

The algorithm for perceptron training (i.e., weight adaptation) can be summarized in the following steps:

Step 1. All weights $W_{m,i,j}$ are initialized to small random values;

Step 2. An input vector $I_1, I_2, \ldots, I_P$, is presented together with its corresponding desired output vector $o_1, o_2, \ldots, o_Q$;

Step 3. On the basis of the input, the actual output of each PE for each layer is computed using Equation 1. If a sigmoid activation function is used, then the output is given as

$$o_{m,n}(t + 1) = \frac{1}{1 + e^{-(\beta_n - \theta_n)}} \tag{6}$$

where

$$\beta_n = \sum_{k=1}^{N_{m-1}} o_{m-1,k}(t) W_{m-1,k,n}(t)$$

Step 4. The error between the desired output and the actual output for each PE, computed from Equation 2 or 3, is used to adjust the weights as given in Equations 4 and 5. For a sigmoid activation function, Equation 5 simplifies to

$$\Delta W_{m-1,i,j}(t + 1) = \eta e_{m,j} o_{m-1,i} o_{m,j}(1 - o_{m,j}) \tag{7}$$

Convergence is sometimes achieved faster if a momentum term is added and weight changes are computed as a function of the previous adjustment, i.e.,

$$\Delta W_{m-1,i,j}(t + 1) = \eta e_{m,j} o_{m-1,i} o_{m,j}(1 - o_{m,j}) + \alpha \Delta W_{m-1,i,j}(t) \qquad 0 < \alpha < 1 \tag{8}$$

where α is the momentum rate.

Steps 2 to 4 are repeated for each training input as many times as is necessary to achieve convergence, i.e., until the error between computed and desired outputs for each PE for each training pattern is reduced to the maximum allowable.

A number of factors influence the rate of convergence of the algorithm. For example, the higher the value of the learning rate, η, the faster the algorithm may converge but the higher the likelihood of instability, i.e., it may lead to oscillations. Hence one needs to select a value of η big enough to speed up convergence but small enough not to cause instability. A similar tradeoff is required in selection of α. Threshold values θ_n also affect the rate of convergence, although not in an obvious way. One may often choose to use trainable threshold values, starting with random assignments of threshold values for each PE and updating them during the training process in the same way the weights $W_{m,i,j}$ are trained, i.e.:

$$\Delta\theta_{m,j}(t + 1) = \eta e_{m,j} o_{m,j}(1 - o_{m,j})(t) + \alpha \Delta\theta_{m,j}(t) \tag{9}$$

CASE STUDY

The objective of this preliminary case study was to train a three-layer perceptron to classify 32 × 32 pixel pavement images by type of cracking, in this case to identify whether a given image displays transverse or longitudinal cracking. These images are components of 512 × 512 pixel real pavement images (Figure 5).

Although in practice images acquired in the field are of much larger dimensions, typically 512 × 512, the 32 × 32 pixel-sized images were selected for this initial study mainly because one of the original objectives was to investigate the performance of the perceptron, and the smaller size images reduce the computational burden, and hence speed up the learning and testing processes. Also, because the feature extraction procedure does not preserve the relative positions of

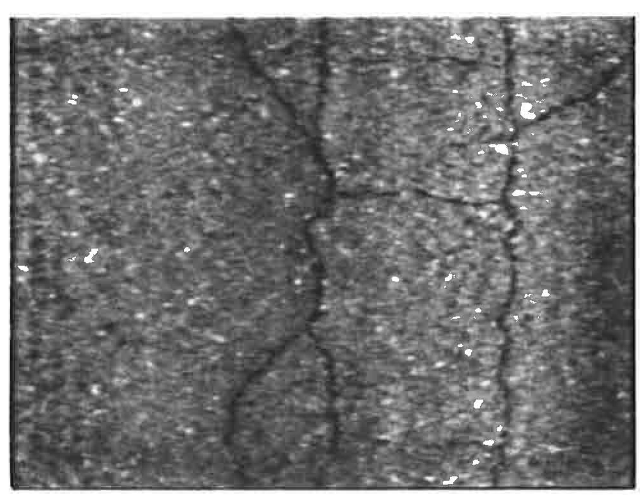

FIGURE 5 Typical 512- × 512-pixel pavement image.

the distresses on the image (only identifying the general orientation of the distresses), doing the processing in two steps may be advantageous, first processing 32 × 32 segments, or tiles, of the images, and then linking the results from the various tiles. In this way, the relative positions of cracks in the 512 × 512 image can be much more easily preserved. For this study, 20 512 × 512-pixel, 8-bit gray scale images each representing 2 × 4-ft images of asphalt concrete pavement were provided by Roadman-PCES, Inc. The images represented different types of surface distress, mainly transverse, longitudinal, and alligator cracking.

In order to prepare a set of 32 × 32 pixel training subimages (each subimage representing a 1.5- × 3-in. pavement image), each of the 512- × 512-pixel images was partitioned into 32- × 32-pixel binary images by simple thresholding, whereby a pixel was given a value 1 if its gray scale value was less than the threshold, indicating a distressed pixel, or 0 otherwise. Then 256 of these subimages were carefully selected to form the set of training images, each consisting of one of four types of distress, namely, no distress, transverse cracking, longitudinal cracking, or combination distress, the last representing diagonal cracking, random cracking, patches, etc. Because these subimages were small, an alligator cracking classification could not be used because such distress could only be observed from the 512 × 512 images. The allocation of these subimages to their actual classification in the training set was performed by manual inspection and a majority vote of three observers, on the basis of the display of each digitized subimage on the computer monitor.

A set of features was extracted from each subimage to form an input vector for perceptron training. The features were based on summary row and column statistics for each image and included

- Mean number of distressed pixels per row or column of a subimage,
- Variance of the number of distressed pixels per row,
- Variance of the number of distressed pixels per column,
- Mean number of runs per row,
- Mean number of runs per column,
- Mean run length per row, and
- Mean run length per column.

A run is defined as an uninterrupted sequence of distressed pixels in one direction, and run length is the number of pixels in a run. Currently, only the first three features are used for training and testing of the perceptron, but additional features may later be included when classification of the images is expanded to include severity and extent of distress. This feature extraction approach has been pursued in preference to a direct approach, whereby each pixel of an image is an element in the input vector to the perceptron. The two main reasons for this, which were verified in an earlier study using hypothetical images, are that

- A smaller number of training samples is required since the features provide better characterization of the distinction between different types of cracking in the images; and
- The size of input vector is reasonably small and independent of the size of the images, thus facilitating faster learning for the perceptron.

Software implementation of the three-layer perceptron for the case study was developed in C on a SUN-SPARCstation. Convergence of the perceptron during training was achieved using trainable threshold values for the PEs and low values of η and α of between 0.1 and 0.2. It generally required 18,000 iterations for the system to converge, which took about 4 to 6 hr on the SUN-SPARCStation. An iteration is one round of presentations of the training samples. The system was said to have converged when the average error between the computed and desired output of the PEs was reduced to 0.05. It took about 5 sec to classify the 256 tiles of one 512 × 512 pixel image.

In order to evaluate the performance of the perceptron in classification of the tiles, each tile was processed by the perceptron and its classification was compared to its human visual classification, or actual classification. Table 1 presents the comparison between the actual and perceptron results for the training set of 256 tiles; Table 2 presents the results for a test set of 4,864 tiles; and Table 3 presents the results for the combined set of 5,120 tiles.

Clearly, the 100 percent correct classification of the perceptron for the training set is impressive. (Recall that a feature vector of only three simple features was used.) Performance

TABLE 1 PERFORMANCE OF THE PERCEPTRON ON CLASSIFICATION OF THE TRAINING SET

Actual	none	trans	long	comb	Total	%-corr
none	143				143	100%
trans		66			66	100%
long			36		36	100%
comb				11	11	100%
Total	143	66	36	11	256	

TABLE 2 PERFORMANCE OF THE PERCEPTRON ON CLASSIFICATION OF THE TEST SET

Actual	none	trans	long	comb	Total	%-corr
none	4389	33	9		4431	99%
trans	7	132		3	142	93%
long	10		233		243	96%
comb	9	6	4	29	48	60%
Total	4415	171	246	32	4864	

TABLE 3 PERFORMANCE OF THE PERCEPTRON ON CLASSIFICATION OF ALL THE TILES

Actual	none	trans	long	comb	Total	%-corr
none	4532	33	9		4574	99%
trans	7	198		3	208	95%
long	10		269		279	96%
comb	9	6	4	40	59	68%
Total	4558	237	282	43	5120	

on the much larger test set resulted in correct classifications for 99 percent of the nondistressed tiles, 93 percent for transversely cracked tiles, and 96 percent for the longitudinally cracked tiles. These results were also excellent.

The classification results for tiles with combination distress were not as impressive, achieving only 60 percent correct classification on the test set, even though 100 percent correct classification was achieved for the training set. This result is probably because of several factors including the small size of the training set and the fact that this distress type includes various distress patterns that do not have homogeneous characteristics. Another reason is the presence of a lot of noise in the tiles, which made it difficult even for the human observers to classify some of the tiles. Possibilities for improving the performance of the model in classification of this class of distresses include increasing the training set size, reducing noise in the images before the training and classification process, and splitting this classification into two or three separate classes. For example, diagonal cracking, random cracking, and patches could all be separate classes.

Overall, however, these initial results are most encouraging.

CONCLUSIONS

A potential automated pavement evaluation system to address multisensor applications; integrate different types of sensors, techniques and information; and offer more sophisticated, intelligent processing capabilities for improved pavement management has been described. The results of the case study indicate the potential for application of neural network models for distress classification of pavement images as part of the proposed INDE system. More work needs to be done to improve the accuracy and speed of the classification process. For example, there is need to incorporate image preprocessing to reduce noise in the images. Inclusion of additional features, proper selection of training examples, and use of other types of neural network models also needs to be explored. In addition, the potential for real time application of such a system may well depend on effective hardware implementation of the system.

In the next stage of this research, classification of the 32- × 32-pixel images will be refined to include severity and extent of distress. Integration of the results of these 32- × 32-pixel images for classification of an entire 512- × 512-pixel image will also be explored. Ultimately, evaluation and analysis of the system for field implementation, including hardware implementation and use of standard pavement surface distress data collection and reduction criteria, will be investigated.

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