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ABSTRACT

This paper discusses a novel approach for composite damage assessment with potential for DoD, NASA, and commercial applications. We have analyzed and modeled a two dimensional composite damage assessment system for real-time monitoring and determination of damage location in a composite structure. The system combines two techniques: a fiberoptic strain sensor array and an optical neural network processor. A two dimensional fiberoptic sensor array embedded in the composite structure during the manufacturing process can be used to detect changes in the mechanical strain distribution caused by subsequent damage to the structure. The optical processor, a pre-trained Kohonen neural network, has the capability to indicate the location of the damage due to its positionally associative architecture. Because of the parallel, all optical architecture of the system, the system has the advantages of having high resolution, a simple architecture, and almost instantaneous processor output. Results of the modeling and simulation predict a highly robust system with accurate determination of damage location. We are currently beginning work on a breadboard demonstration model of the system.

1. INTRODUCTION

Recent advances in material science have spurred the development and use of composite materials in a wide range of applications from rotorcraft blades and advanced tactical fighter aircraft to ocean and space structures. Mechanically, composite materials are much more complex than their metal alloy predecessors, and are much more difficult to reliably analyze. In the case of impact damage, for example, the external surface appearance of the composite may appear normal but internal damage can be extensive, including composite delamination. These types of failures make nondestructive evaluation and health monitoring of such materials difficult but critically necessary. Being able to predict structural failures far enough in advance to prevent them and to provide real-time structural health and damage monitoring is becoming a realistic possibility. Conventional sensors and digital processors, although highly developed and well proven in other applications, may not be the most suitable for composite structures[1]. We have modeled a system incorporating a fiberoptic sensor array; and an optical neural network processor.

The system concept modeled and simulated is shown in Figure 1. Figure 2 is a system block diagram. Light from a laser diode is coupled through a star coupler into a fiberoptic strain sensor array. Damage at a particular spatial location in the composite produces a unique strain distribution which results in a unique set of sensor output light intensities. This set of signals becomes the input to the neural network. The light from each optical fiber is projected through an array of transparencies whose transmissivities are equal to the weight values determined for the network during the training process The weighted light from all the fibers is projected onto an image screen corresponding to the neural plane. The weighted light intensities add at the image screen, therefore the brightest area on the screen corresponds to the neuron that would"fire". The training determines the appropriate weight values to ensure that damage occuring at a particular location on the composite causes a bright spot to be produced at the same relative location at the image(neural) plane.

Fiberoptic sensors were chosen because of their advantages over other types: they are small in diameter, light weight, EMI/EMP resistant, have high bandwidth, and can be used to monitor large areas when used in a distributed sensing configuration. Their small diameter allows them to be embedded within a composite structure during the manufacturing process with a minimum of structural degradation. The fiberoptic sensors chosen are polarimetric, although other types, such as few mode, could also be used. Strain produces a modulation of the output polarization which is then converted to an intensity modulation by a polarizing analyzer. The sensors are configured into an array of fibers aligned along the two horizontal coordinate directions. A unique strain distribution will be formed corresponding to a particular damage location; the strain sensor array will thus produce a unique set of output

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intensities associated with this damage location. This results in a one to one correspondence between the damage location coordinates and the set of sensor array output intensities which can be exploited by an artificial neural network processor.

The output light intensities from the fiber array are processed in parallel by an Kohonen optical neural network. Once trained, the neural network can calculate the correct outputs almost instantaneously, the delay being the time for light to propagate from the ends of the fibers to the image screen, ie. approximately a nanosecond. The neural network was simulated and training accomplished off-line by proprietary computer software. The weights between the inputs and outputs are representative of the desired input-output relationship and are determined by the training process. The neural network processor is a Kohonen architecture which has a single layer, parallel structure. The Kohonen neural network has the capability to classify outputs from the fiber sensors into desired clusters in the network[2,3]; the desired cluster being at the same relative spatial location in the neural plane as the damage in the composite plate. Once damage occurs in the composite structure, the fiberoptic sensor array will sense the resultant strain distribution, and produce a particular light intensity pattern. The trained neural network processor automatically associates this light intensity pattern with a pre-defined cluster having same spatial position as the damage. Although the neural network can be implemented by optical, electronic, or hybrid means, we chose the optical implementation for our simulation because of its simplicity and speed and because it is more readily implementable for Kohonen networks than other types. The composite system was simulated using a commercially available finite element software program.

2. FINITE ELEMENT STRAIN ANALYSIS

In order to calculate the static strain distribution of the damaged composite structure for various damage locations, the MSC/NASTRAN program was utilized [4]. The structure analyzed was a portion of the square plate of epoxy-fiberglass composite with dimensions 180x180x0.9 inches as shown in Figures 3 and 4. The plate was assumed to be a 6-ply symmetrical laminate; each ply was 0.15 inches thick with the lamina orientation of -45/45/0/0/45/-45 degrees. One edge of the plate is attached perpendicularly to the surface of a fixed structure, thus displacements caused by the damaged plate are not transferred onto the rigid structure. The other three edges are free edges. The damage was considered to be equivalent to a 400 lb external force applied perpendicularly at the desired location on the surface of the plate.

The plate was divided into 1,296 equal elements, each of them of dimension 5.0 by 5.0 inches. In addition, each element was connected to its immediate neighbor elements at their nodes. To reduce the amount of data and processing time, the QUAD4 type of element was selected. Although it is less accurate than the 8-noded QUAD8 element, it provided sufficient accuracy. For a given damage location, the NASTRAN program computes mechanical displacement as well as strain values for each finite element in the composite structure. Thus the strain distribution is formed by combining all discrete strain values on the elements. Both x- and y-oriented strain values were calculated. The maximum strain value- 200 microstrain is located near the center of the applied force; the strain values decrease to approximately zero at 40 inches away. The area monitored in the simulation was a square 90 by 90 inches centered on the plate as shown in figure 4. This central range corresponds to the extent of the neural network processor layer.

3. POLARIMETRIC SENSOR ARRAY

The two dimensional fiberoptic sensor array is operated in the polarimetric mode. The polarimetric sensor was chosen because of its simplicity and it strain sensitivity. As shown in Figure 5, 24 fiberoptic sensors were assumed arranged in a two dimensional array on the composite structure. There were 12 sensors in each direction with equal separations between fibers of 15 inches. The fiberoptic sensors were assumed to be illuminated by a laser diode with equal light intensities. The undamaged(no strain) system was defined as having zero output light intensity for each fiber sensor, and unity output light intensity for maximum axial and lateral strain values of 150 and 1,700 microstrain respectively.

Mechanical strain is directly related to the change of the measured output light intensity[5]. When damage occurs, physical displacement of the material will occur. As a result, a particular mechanical strain distribution will be formed depending on the damage location. This strain distribution can be considered as a two dimensional strain pattern in the composite structure. The embedded fiber sensor array will "sense" this strain pattern by its x and y axial fiber components, and will produce a particular light intensity pattern. Consequently, this particular damage location can be identified by this light intensity pattern. For a fiber used in the polarimetric mode, the induced phase difference of the light between eigenaxes, $\Delta\Phi$, can be directly related to the applied strain ε by a constant k expressed as:

$$I = I_0 \cos^2\left(\frac{k\varepsilon + \pi}{2}\right) \quad \text{and} \quad \Delta\Phi = k\varepsilon$$

To detect a two dimensional strain distribution on a composite plate using a polarimetric sensor array, not only the axial (longitudinal) but also lateral (transverse) intensity-strain relationship of fiber must be known. For this reason, two experiments were performed[6] to measure the strain sensitivity for both axial and lateral strain. The experimental results showed that the output light intensity was a sinusoidal function of applied strain for both cases, as expected, and the sensitivity of the fiber sensor due to transverse strain on a 5 inch segment was about 11 times less than that due to longitudinal strain as illustrated in figure 6. Mathematically, the intensity-strain relationship for both cases in figure 6 can be expressed respectively as:

$$I = I_0 \cos^2\left(\frac{k_l \varepsilon + \pi}{2}\right)$$

$$I = I_0 \cos^2\left(\frac{k_t \varepsilon + \pi}{2}\right)$$

where: k_l = constant for longitudinal case = 0.019997
k_t = constant for transverse case = 0.001815

Using the results of the finite element analysis, the strain values in both coordinate directions were used to determine the total strain experienced by each fiber. The strain seen by each fiber is calculated differently depending on whether the strain is longitudinal or transverse. Both values can be written, respectively, as:

$$\varepsilon_{ave} = \left(\sum_{i=1}^{n} \varepsilon_{i-l}\right) / n$$

$$\varepsilon_{sum} = \sum_{i=1}^{n} \varepsilon_{i-t}$$

where: n = number of elements along each fiber sensor

Combining the above equations, the total phase change of light caused by both longitudinal and transverse strain is immediately obtained.

$$\Delta\Phi_l = k_l \, \varepsilon_{ave}$$

$$\Delta\Phi_t = k_t \, \varepsilon_{sum}$$

$$\Delta\Phi_{total} = \Delta\Phi_l + \Delta\Phi_t$$

The output light intensity from the polarizer can be determined from the following equation:

$$I = I_0 \cos^2\left(\frac{\Delta\Phi_{total} + \pi}{2}\right)$$

The calculation of the output intensity values of each fiber sensor with different damage locations were done by a computer simulation program[4].

4. OPTICAL NEURAL NETWORK-BASED PROCESSOR

The processor simulated is a parallel optical processor consisting of a pre-trained, supervised Kohonen neural network which has the capability to classify the patterns of fiber sensor outputs into the desired clusters having same relative spatial positions with respect to the particular damage location in the composite structure as shown in Figure 7. The neural network is a computing system made up of a number of simple, highly interconnected processing elements called neurons, which processes information by its response to external inputs[7]. The strength of the interconnections in the network are the weights. Learning in a neural network is a process by which the weight values ore optimized by a specific learning rule. Actually, the neural network can be considered as an intelligent processing unit with a certain number of inputs and outputs, that can be trained to produce the desired transfer function. The neural network stores the trained input-output relationship by its weight distribution, but also has the capability to make its own decision on untrained inputs according to the "knowledge" it acquired in training.

The Kohonen neural network shown in figure 7 is an important architecture used extensively in the artificial neural network community. Its learning process can be either supervised or unsupervised depending on the application. Generally, the supervised Kohonen neural network is used as a pattern classifier with artificially defined clusters, while the unsupervised network is usually suitable for statistical analysis with naturally formed clusters[2,3,8]. A prerequisite of using the supervised model is that the class-affiliation of the input patterns must be known[9]. Each desired cluster can have one or more neurons. The size of the neural network is related to the number of separable input patterns needed to be classified and the desired accuracy. During training, with small initial random weight values, each neuron in the network has to compete to respond to a particular input pattern by comparing the Euclidean distance between its weight and input vectors:

$$\|X - W_{winner}\| = \min\|X - W\|$$

where **X** and **W** are input and weight vectors respectively. The winner is the neuron which has the minimum Euclidean distance, in the other words, the winner's weight vector is closest to a particular input vector. Only the winner gets to update its weights depending upon its position in the network. If the winner is located within the desired cluster, which means that corresponding input pattern maps into a correct category, the winner's weight vector will be moved closer to that input vector by adding a fractional difference of the input and weight vector.

$$W_{winner}(t+1) = W_{winner}(t) + a(t)[X(t) - W_{winner}(t)]$$

where a(t) is a time-dependent decreasing learning rate ($0 < a(t) < 1$). If the winner is located outside the desired cluster, which means that corresponding input pattern falls into a wrong category, the winner's weight vector will be moved farther from that input vector by subtracting the same fractional difference.

$$W_{winner}(t+1) = W_{winner}(t) - a(t)[X(t) - W_{winner}(t)]$$

From the network viewpoint, the training process can be considered as the winner's movement around the network. After sufficient training iterations, each winner of an individual input pattern settles down inside its desired cluster, and the weight vectors over the entire network are optimized relative to an input set. The fixed weight values represent the desired input-output relationship. Once a trained pattern or a similar untrained pattern appears, the network automatically knows what this pattern is, or how this pattern should be classified.

Unfortunately the standard learning rule involves a long training process, especially, when a large number of desired cluster are required. The larger the number of desired clusters is, the smaller the initial probability of any particular input pattern matching its desired cluster will be. We have developed a modified learning rule for the training of supervised Kohonen neural networks which overcomes this drawback by increasing the probability of any particular pattern matching its desired cluster[10]. The new learning rule is identical to the original one when a winning neuron of a particular input matches its desired cluster, but it is modified when the winning neuron of an input does not match its desired cluster. When a mismatch occurs, the new learning rule not only adjusts the winner's weight vector farther from that particular input, but also, at the same time, updates the weight vector of the desired cluster by moving it closer to that input vector. For the mismatched case the modified learning rule is:

$$W_{winner}(t+1) = W_{winner}(t) - a(t)[X(t) - W_{winner}(t)]$$

and

$$W_{d.c.}(t+1) = W_{d.c.}(t) + a(t)[X(t) - W_{d.c.}(t)]$$

where subscript **d.c.** refers to the desired cluster. The operation of the new learning rule can be viewed as a "push-pull" process. Whenever a mismatched case occurs, the winner is pushed away from its current location by reducing the local sensitivity to a particular input. At the same time, the winner is also pulled toward to its desired cluster by increasing the local sensitivity of the desired cluster to that input. Mathematically, the new learning rule increases the general probability of any particular input matching its desired cluster. Physically, the winner's movement around the network controlled by the new learning rule is directly guided while it is indirectly guided under the original rule. With the modified learning rule, the network was successfully trained with a factor of 700 decrease in training time as compared to the standard learning rule.

After the strain distributions were calculated and the optical intensity patterns from the fiber sensor array determined, we trained the computer simulated neural network to classify these patterns into the desired spatial clusters in the network. The training data were the normalized output light intensity values of the fiber sensors corresponding to the damage locations . The number of input elements of the neural network depends on the number of fiber sensors embedded in the composite structure, in this case 24. A single layer neural network was constructed according to the simulation results of the composite structure and the arrangement of fiberoptic sensors described earlier. A 64 (8 by 8) neuron array was arranged with equal separation within a square of 90 by 90 inches in which damage could occur. Each neuron on the Kohonen layer represented a single damage point having the same relative two dimensional position with respect to the neural network. In other words, each neuron consists of a desired single-neuron cluster to classify damage appearing in the same spatial location as neuron in the network as shown in Figure 5.

The 64 sets of training data were prepared corresponding to the 64 selected damage locations, each of them was represented by the corresponding light intensity pattern from the embedded fiberoptic sensor array. Each set of inputs had 24 values corresponding to the 24 optical fiber sensor array outputs. Consequently, the neural network processor had 24 inputs and 64 outputs. Each set of input data was randomly fed into the neural network during the training process. The training process started with the learning rate of 0.05, and the weights were optimized with respect to the whole input pool at 2,048 iterations, with a learning rate down to 0.04. The optimization process for the weights is shown in figure 8. At the beginning, no inputs matched their desired clusters because of the initial random weights. After about 900 iterations, the number of matched inputs grew rapidly. The training process finally was terminated when the complete set of inputs matched their desired clusters after 2,048 iterations. After training, the fixed weight distribution of the entire network becomes the representation of the relationship between the light intensity patterns and the damage locations.

The optimized weight values can be implemented by use of transparencies having optical transmissivity values equal to the weight values. The bigger the weight value is, the larger the light transmissivity would be. The output light beams from 24 fiber sensors could be partially collimated by a set of lenses. Each beam would then illuminate the whole image screen after passing through its transparency. Each output intensity will produce a specific intensity distribution on the screen . The sum of the 24 individual intensity distributions will form a feature map on which one brightest point will occur. This brightest point is located in the same relative spatial position as is the damage in the composite structure. In other words, for a particular image pattern from fiber sensor array, which is the optical representation of the damage location, there is a brightest point at its desired spatial position on the image screen as shown in figure 9. This brightest point is the damage point we want to locate. The combined image on the screen also can be captured by a camera or CCD array and then can be displayed on a video monitor after any desired image processing, such as thresholding, is performed.

5. SIMULATION RESULTS

The simulation resulted in 100% of the training inputs correctly classified into their desired clusters.The trained neural network was then tested by using untrained damage inputs. We picked 128 sets of untrained inputs, which corresponded to 128 damage locations different than the trained inputs. The testing results showed that all of the untrained inputs were correctly classified to the closest cluster. The trained neural network processor was also tested with noisy inputs. The noise values, which can be considered as variations in either input or weights, were varied from 0% to 21% with respect to the training inputs. The results shown in Figure 10 show that all trained damage inputs with up to 15% noise will still be associated with their desired clusters which means the processor will operate normally. With 18% and 21% noise, the accuracy degraded to 75% and 52% trained damage inputs classified into their desired clusters. Thus the trained network processor appears to be extremely robust.

6. CONCLUSIONS

The composite damage assessment analyzed is a real-time 2-D damage monitoring system. To date, this system has been modeled and the operation simulated on the computer. The system combines two techniques in a unique way: a fiberoptic strain sensor array and an optical neural network-based processor. The system is operated with a purely parallel optical architecture without any intervening conversion between electrical and optical signals. Therefore, high processing speed and almost instantaneous response are predicted. The system also could be developed further as a three dimensional damage monitoring system. Other plans for further development include multiple-damage assessment. In a multiple-damage situation, the multiple clusters of the neural network processor will indicate the damage locations for the strain distribution caused by multiple-damage in the composite structure. In addition, we are beginning to build a breadboard system for evaluation. It has been recognized that neural network processors are attractive for many other types of fiberoptic sensors and sensor arrays. Research and development in neural network processed fiberoptic sensor signals is underway at the Center for Fiberoptic Sensor Systems and Smart Structures at Florida Institute of Technology[6,11].

7. REFERENCES

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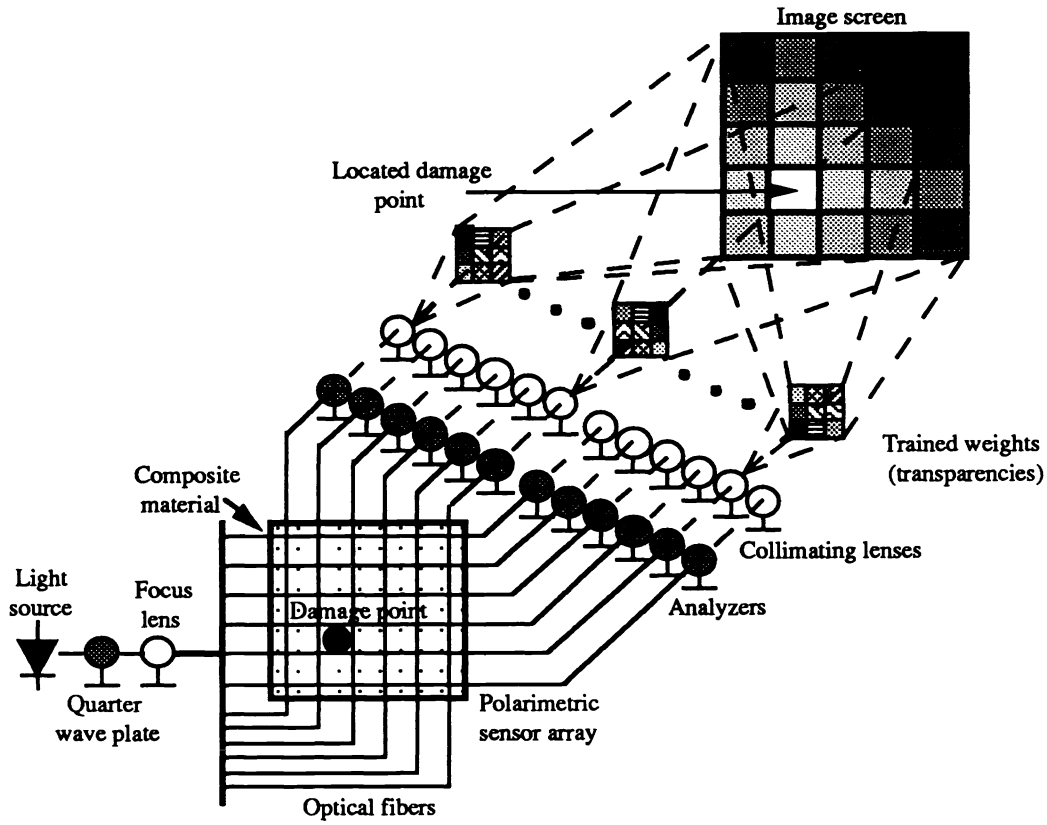

Figure 1. Schematic of all optical 2-D damage assessment system

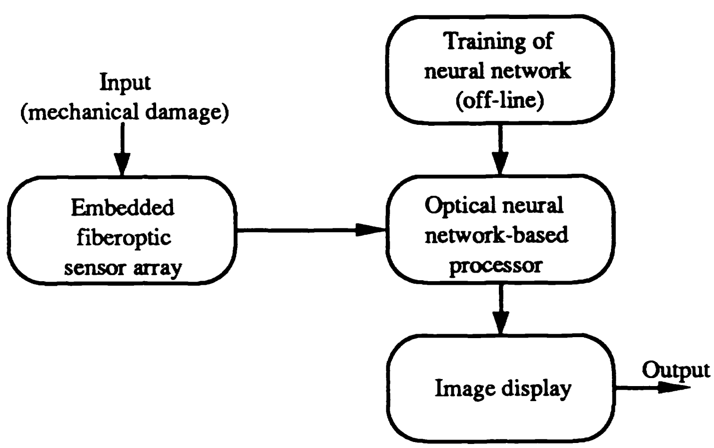

Figure 2. System block diagram

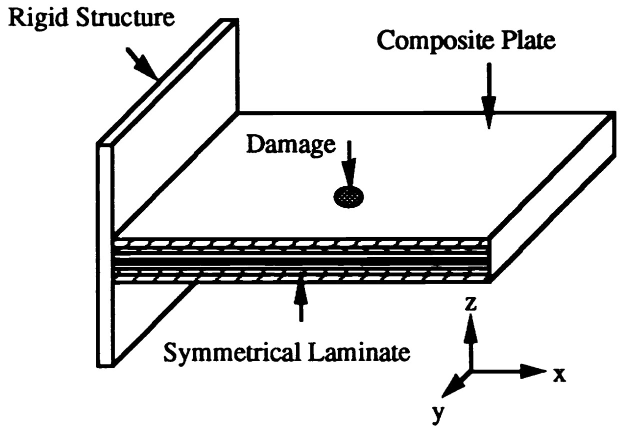

Figure 3. Simulated composite structure

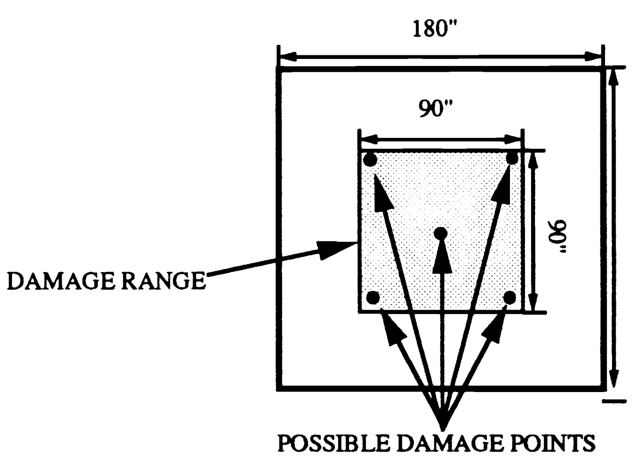

Figure 4. Composite plate and damage area

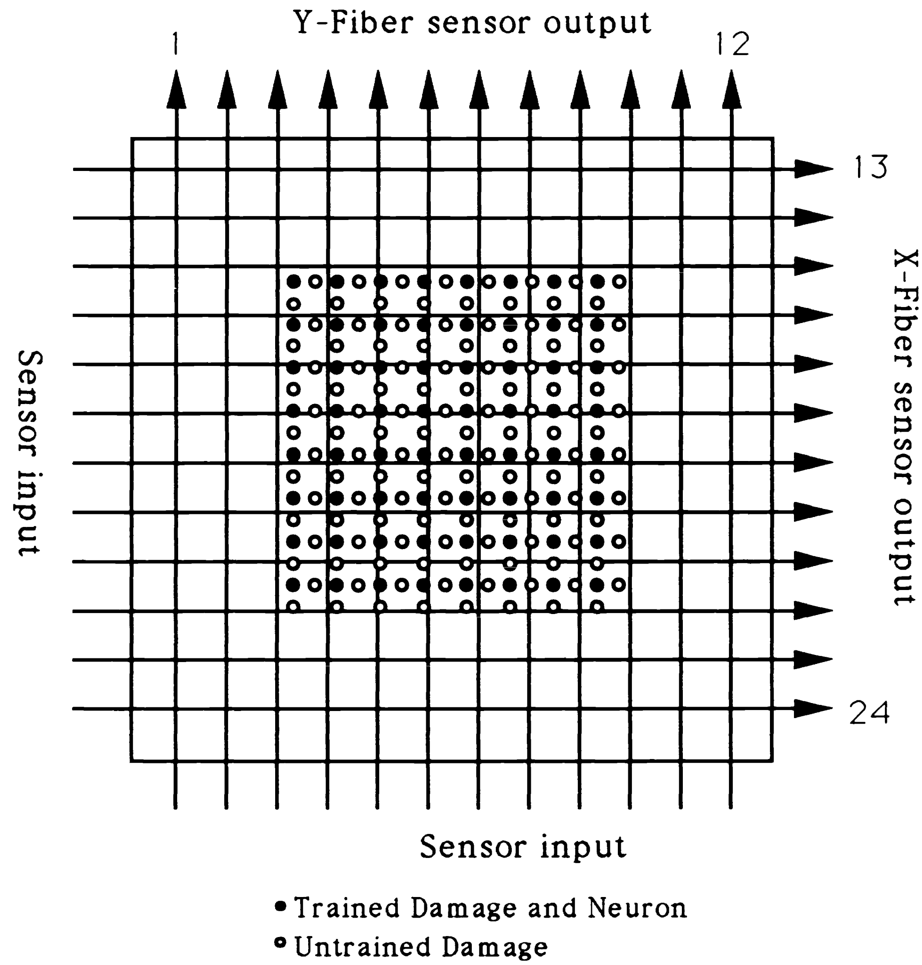

Figure 5. Sensor array configuration and neuron/damage locations

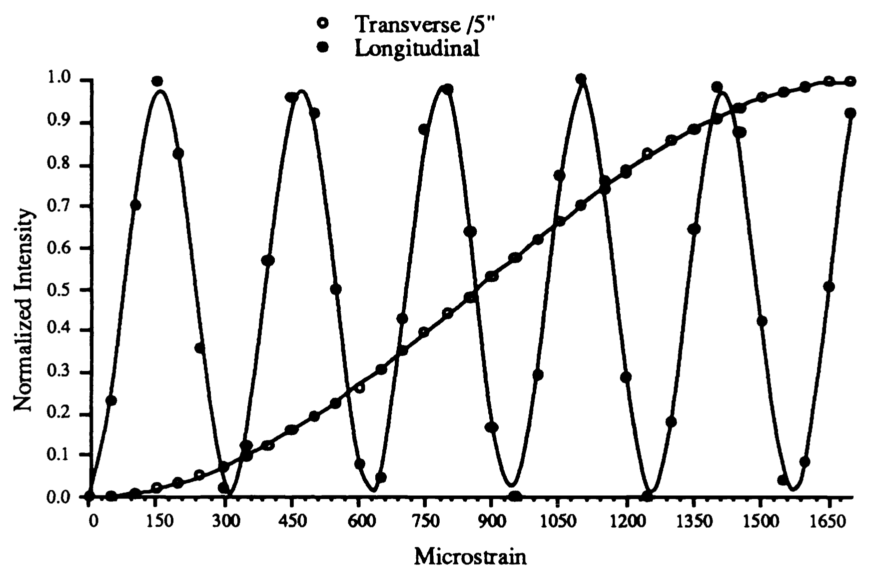

Figure 6. Measured strain sensitivity of polarimetric sensors used in simulations

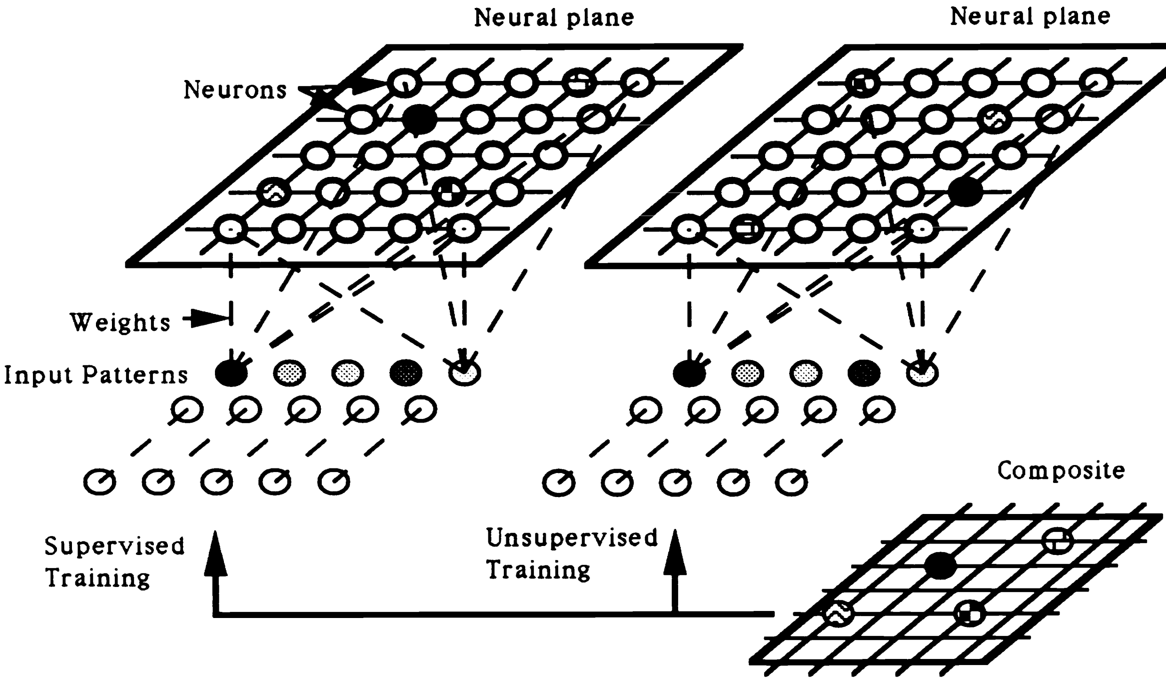

Figure 7. Kohonen neural network

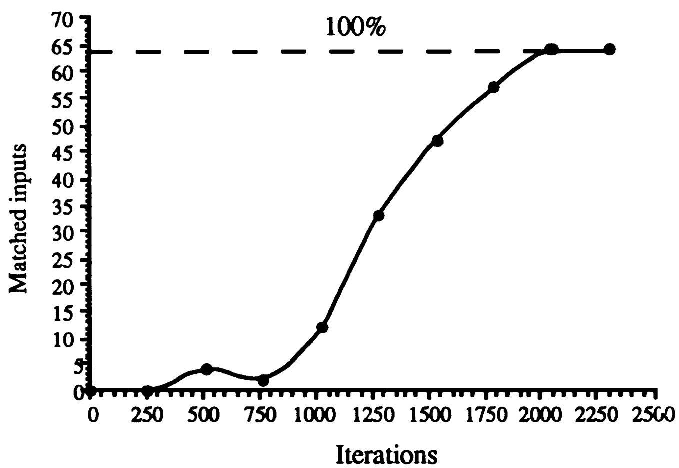

Figure 8. Correctly matched training paterns-vs-training cycles

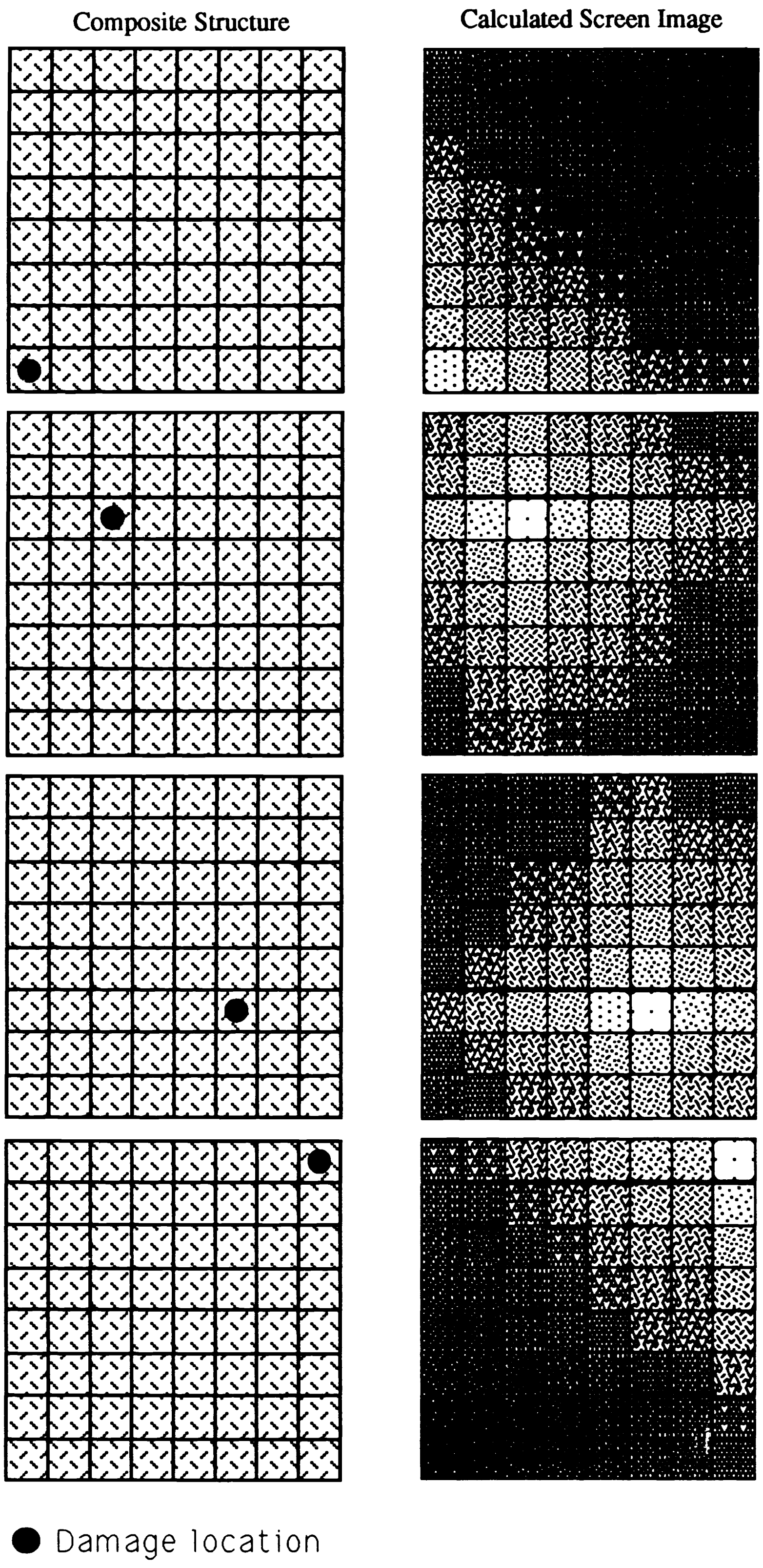

Figure 9. Comparison of damage location and predicted image intensity distribution

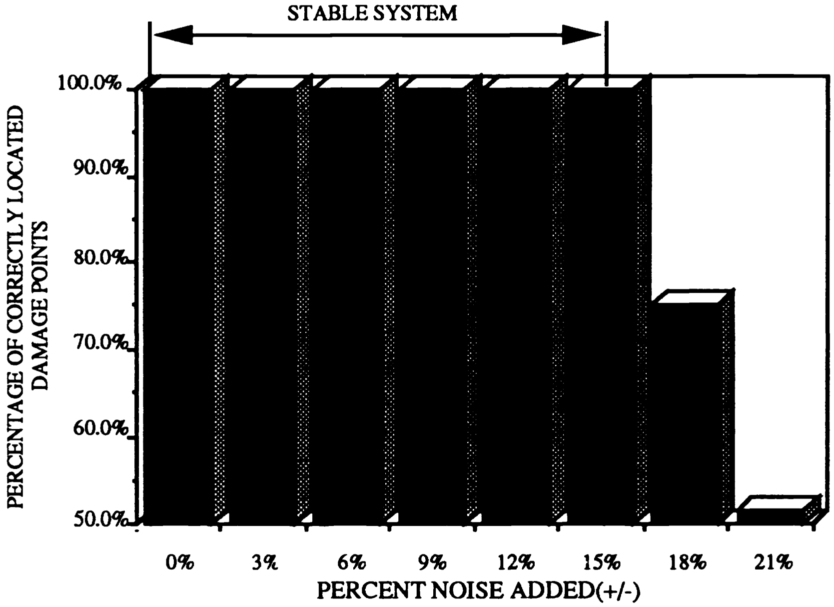

Figure 10. Effect of noise on classification accuracy