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ABSTRACT

Vibration monitoring of components in nuclear power plants has been used for a number of years. This technique involves the analysis of vibration data coming from vital components of the plant to detect features which reflect the operational state of machinery. The analysis leads to the identification of potential failures and their causes, and makes it possible to perform efficient preventive maintenance. Early detection is important because it can decrease the probability of catastrophic failures, reduce forced outgage, maximize utilization of available assets, increase the life of the plant, and reduce maintenance costs.

This paper documents our work on the design of a vibration monitoring methodology based on neural network technology. This technology provides an attractive complement to traditional vibration analysis because of the potential of neural networks to operate in real-time mode and to handle data which may be distorted or noisy. Our efforts have been concentrated on the analysis and classification of vibration signatures collected by Electricite de France (EDF). Two neural networks algorithms were used in our project: the Recirculation algorithm and the Backpropagation algorithm. Although this project is in the early stages of development it indicates that neural networks may provide a viable methodology for monitoring and diagnostics of vibrating components. Our results are very encouraging.

BACKGROUND

A power plant (nuclear or fossil) is fundamentally a thermodynamic system that includes a heat source (fission or combustion), flowing fluids, valves, control systems, and rotating machinery (pumps, fans, motors, gear boxes, turbines and a generator.) Although the flow of fluids (water and steam) can induce vibrations and shock, the primary source of vibrations is rotating machinery. Vibration <u>per se</u> is not necessarily bad if its amplitude and the associated forces are within acceptable limits. Indeed, vibration in machinery can be the source of much information about the various systems involved.

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There is a great deal of literature available that describes the type of vibration signals to be expected for faults in typical systems and the analysis techniques that can be used for early detection of faults. Angelo[1] presents a discussion on actual phenomena and their individual characteristics. For example, the low frequency domain contains information about unbalance, misalignment, instability in journal bearing and mechanical looseness; analysis of the medium frequency range can render information about faults in meshing gear teeth while the high frequency domain will contain information about incipient faults in rolling-element bearings. In addition, trend analysis may be performed by comparing the vibration spectrum for each machine with a reference spectrum and evaluating the vibration magnitude changes at different frequencies.

This form of analysis for diagnostics is often performed by maintenance personnel monitoring and recording transducer signals and analyzing the signals to identify the operating condition of the machine. This method has proven to be effective in identifying potential failures before they occur. With the advent of portable fast Fourier transform (FFT) analyzers and "laptop" computers, it is possible to collect and analyze vibration data on-site and detect incipient failures before repair is necessary. Indeed, it is often possible to estimate the remaining life of certain systems once a fault has been detected. Hence, there is considerable motivation to design systems to automatically perform this analysis on a real-time basis in a reproducible manner.

METHODOLOGY

RMS velocity, acceleration, displacements, peak value, and crest factor readings can be collected from vibration sensors attached to plant machinery. The sensors are placed at locations where the signals are expected to be reliable. From these data, spectra are generated using FFT techniques and analyzed by expert personnel to identify faults. Our goal is to design a diagnostic system using neural network technology. A system such as this would automate the interpretation of vibration data coming from plant-wide machinery and permit efficient on-line monitoring of these components.

A network of artificial neurons (usually called a neural network) is a data processing system consisting of a large number of simple, highly interconnected processing elements in an architecture inspired by the structure of the cerebral cortex portion of the brain. As a result, neural networks are often capable of doing things which humans or animals do well but which conventional computers often do poorly. For example, neural networks have the ability to recognize patterns, even when the information comprising these patterns is noisy, sparse, or incomplete.

Perhaps the most important characteristic of neural networks is the ability to model processes and systems from actual data. The neural network is supplied with data and then "trained" to mimic the input-output relationship of the process or system. Neural networks also have the ability to respond in real-time to the changing system state descriptions provided by continuous sensor inputs. For complex systems involving many sensors and possible fault types, real-time response is a difficult challenge to human operators; neural network technology may provide a viable alternative to the solution of this problem.

VIBRATION SIGNATURES

To perform spectral monitoring of components in an operating engineering system, signatures are collected from plant machinery and analyzed to detect features which reflect the operational state of the machinery. Our data consist of vibration measurements collected from ball bearings of type 6206 during an aging simulation process. The rolling element under test is mounted on a horizontal shaft (fed by a 10 KW motor) and charged radially by means of a jack, imposing a vertical force on the bearing. These conditions generate scaling faults on the component. The geometry of a 6206 bearing is depicted in Figure 1. Data is collected using an accelerometer placed in the radial direction to the loading zone of the bearing -- the accelerometer is screwed onto a flange, the flange is in turn stuck to the rolling element. From these measurements, spectra are generated using FFT techniques. Spectra are averaged over 16 samples with a HANNING window. The spectra contain 397 points in the range 5 Hz to 1 KHz.

The acceleration spectra were transformed by means of numerical integration into velocity spectra. Velocity measurements are used because they can be directly compared with alarm and shutdown criteria[2,3] and also because velocity amplitudes are linked to the source of excitation. We are using low frequency spectra (5 Hz to 1000 Hz) because the frequencies generated by severe defects in rolling element bearings are usually in this range. High frequency measurements are linked to incipient faults in the bearings, that is bearing faults in the very early stages of development. Figure 3 depicts a spectrum of a 6206 bearing with a generalized scale fault of the inner race. The data set contains 71 samples representatives of the behavior of rolling element operating under the following conditions: no fault, localized scaling fault of inner race, generalized scaling fault of inner race, localized scaling fault of outer race, generalized scaling fault of outer race, artificial localized fault of a ball, generalized scaling fault of two balls, and generalized scaling fault of all components. Figure 2 shows the inner race of a 6206 bearing with a localized scaling fault.

The spectral values were row-wise normalized in the range (0.1, 0.9). To perform the normalization, the maximum and minimum values for each pattern are calculated and the spectra scaled to the appropriate range. Row-wise normalization is critical for this processing because it ensures that the shape of the spectrum is preserved and, more importantly, that the location of the peaks within the spectra is not altered. The normalized signatures contained 397 points. To reduce the amount of data, we selected the maximum value of every three points and produced signatures containing 132 points (Figure 4). The rationale behind selecting the maximum is the preservation of the original peaks.

NEURAL NETWORKS FOR VIBRATION ANALYSIS

For the analysis of spectral signatures, neural networks may be used both as classifying and clustering systems. To perform classification it is necessary to attach to each signature a label which describes the operational state of the machine at the time of collecting the signature. The input to the network is a spectrum, or its compressed version, and the output is the class label. The network is trained to identify an arbitrary pattern as a member of a state among a set of possible states. Clustering involves the grouping of patterns according to their internal similarity and requires no labels. The aim of clustering is to distribute the set of patterns into states such that the patterns in each state have similar statistical and geometrical properties.

We are addressing the problem of identifying and classifying vibration signatures in two phases. Phase I includes compression of the spectral signatures using Recirculation and Autoassociative Backpropagation networks. Phase II comprises the classification of the compressed patterns using the Backpropagation algorithm. Compression is an important issue in the context of this analysis because we deal with a very large data set and reducing the dimensionality of the patterns decreases significantly the training time and computer resources required.

Recirculation Networks

The Recirculation Network (RNN) algorithm was developed by Geoffrey Hinton and James McClelland[4]. The network is autoassociative in nature and in its simplest version has only two trainable layers, a visible layer and a hidden layer. The input and output layers act simply as buffers for input and output. The network topology is illustrated in Figure 5. The aim of training is to minimize the reconstruction error defined as the difference between the original input vector and the reconstructed vector. The reconstructed vector is assembled by running the compressed representation through the set of weights. This error is an accurate indicator of performance because it is the sum of the squared error at each node. The algorithm minimizes this error using a gradient descent strategy.

The purpose of training is to construct in the hidden layer a representation of the data presented at the visible layer (the input vector.) If the number of hidden units is less than the number of visible units and if the network is trained successfully, the hidden representation may be considered as a compressed version of the visible representation. Under these conditions the network acts as an encoder which maps the original vectors to a smaller dimensional space while preserving their statistical characteristics. For this project we built a network with a hidden layer containing a third of the nodes in the input layer in order to reduce the dimensionality of the input vector set by a factor of three. The network takes as input a 132-point signature and produces a 44-point signature. Higher compression ratios are possible at a higher computational cost and loss of accuracy.

Backpropagation Network

The Backpropagation network (BPN) is a multilayer fully connected network. The algorithm uses the delta rule to compute the weights between connected processing elements so that the difference between the actual output and the desired output is minimized in a least-squares sense. The network may operate in autoassociative and heteroassociative mode. For an autoassociative network, the input vector and the output vector are identical. A heteroassociative network learns associations between input and output pairs which are different. The basic algorithm for Backpropagation is discussed in reference 5.

In the BPN every neuron is connected to all neurons in adjacent layers with no lateral connections. During training the information flows forward from the input layer to the output layer and the error is propagated backwards through the weights to calculate the weight adjustments. Training involves the modification of the weights until the error is reduced to an acceptable limit. The first layer receives the input, modifies it using the set of weights, and passes it to the hidden layer; the hidden layer in turn propagates the modified inputs to the output layer where the overall error is calculated. The hidden layer is used to represent the non-linear characteristics of the data and its size is determined by the complexity of the problem. Figure 6 shows the architecture of a typical three-layer network.

For this project we used the Backpropagation algorithm in its two modes. In autoassociative mode to perform data compression, and in heteroassociative mode to classify the feature vectors. Autoassociative Backpropagation was used as an alternate method to Recirculation for data compression in order to compare the effectiveness of the representations generated by the two methods. The input to the autoassociative network is the 132-point signature and the output is the 44-point compressed signature.

The classification of the patterns was performed using a standard Heteroassociative Backpropagation network which received as input the compressed 44-point signature and produced the class label or rolling element operational states. The network had a 44-node input layer, a 10-node hidden layer and a 6-node output layer. The size of the hidden layer was determined according to the number of possible states (including combinations). Recent studies indicate that the number of regularity features (existing classes) can be used to estimate the number of hidden nodes[6].

RESULTS

For this project, we used the version of the Recirculation network included in NeuralWorks™ which runs on a Zenith 386 SX machine. The Plexi™ implementation of Backpropagation was used for both compression and classification. The program runs on a SUN SPARC IPC workstation.

Compression

Compression was performed using the Recirculation network and the Autoassociative Backpropagation network. The networks have the same topology (132 inputs and 44 hidden units) and were trained on one third of the original data set -- 23 out of 71 patterns. The representations obtained from the two networks are different, each representation is in turn very different from the original spectral signature. An example of the two representations is shown in Figures 7 and 8.

There are three reasons for the difference in representations. First, the weights for the Recirculation network are not required to be symmetrical like the weights in Backpropagation (in Backpropagation the set of weights used in the forward pass W_{ij} is the same as the set of weights used in the backward pass W_{ji}.) Second, the weight adjustment equations and the scheduling of the two algorithms are not equivalent, the RNN algorithm computes the adjustments by considering only local information while BPN computes changes to the weights according to the global error. Finally, the behavior of the Recirculation algorithm approaches gradient descent (the method used by Backpropagation) only after a number of iterations. By the time the behaviors are equivalent, the algorithms are doing search in different regions and continue to look for a solution in separate paths.

The RNN was trained for 50,000 iterations until it reached the pre-established error threshold (0.03.) The compressed signature is geometrically different than the input vector, but retains its statistical properties. We have demonstrated the effectiveness of the compression in previous work by doing clustering of both the original input vector and its compressed representation using the K-means algorithm[7,8]. The Autoassociative BPN was trained for 11,000 iterations to the same threshold (0.03). Usually, the BPN algorithm converges faster for data compression.

Generally, the training of the Autoassociative Backpropagation requires significantly fewer iterations than the training of the Recirculation network. However, the compressed representations obtained from Recirculation are better suited for training the classifiers. Not only is the training of the classifier faster using the compression from Recirculation, but also the representations are better generalizations of the input space.

Classification

Two BPN networks with identical topology were built to perform the classification. One network was trained with the compressed data obtained from RNN, and the second network was trained on data from the Autoassociative BPN. Both networks have as input the 44-point compressed signature generated by the compression networks, 10 hidden nodes, and 6 output units corresponding to each possible operating state. Each state activates a particular neuron in the output layer; for multiple states more than one neuron is activated corresponding to the appropriate combination.

To train the network, 17 patterns representative of every operating state were selected from the total set of 71 (24%). The set also included 7 patterns which had no labels (faults were unknown) because they were collected while the deterioration was evolving from a localized scaling fault of the outer race to a generalized fault of all components in the bearing. To recall, the entire data set was used, including the 7 patterns with unknown faults. The output units have a linear threshold function centered at 0.5. Any output higher than 0.5 is reported as a fault while outputs lower than 0.5 are considered as absence of faults.

Training the classifier using the compressed data from RNN took 23,000 iterations (Figure 9). The error was reduced to 0.01. Of the 64 patterns with known labels, 62 (97%) were classified correctly (two normal patterns are classified as faulty). Of the two misclassified patterns one was classified as having a localized artificial fault of a ball and the other as having a generalized scaling fault of two balls. From the remaining seven (faults were unknown), six were classified as localized scaling fault of the outer race (the condition previous to deterioration) and one was classified as having generalized scaling of the two balls and localized scaling fault of the inner race.

The other classifier converged after 49,000 iterations to the same error (0.01), and used the compressed data from the autoassociative BPN (Figure 10). This network was able to classify correctly 54 of the 64 (84%) patterns with known labels. The misclassified patterns were all non-faulty. Out of the seven patterns without labels, six were classified as having localized scaling fault of the outer race and one as normal.

Representation	No. Iterations	% Error	% Correct Classification
Recirculation	23,000	0.01	97%
Backpropagation	49,000	0.01	84%

Table 1. Classifier Results

We run a set of experiments using a reduced version of the data set (36 patterns representing 4 classes) to evaluate the effect of network topology in training. We used networks with 44 input nodes and 4 output nodes. The size of the hidden layer was set to 16, 6, and 3. We found that decreasing the number of hidden units, increases the number of iterations to the same level of convergence but produces better generalizations. Obviously, an iteration in a small network is faster than for a larger network.

CONCLUSIONS

We are working on the implementation of a methodology for interpreting vibration measurements based on neural networks. The anticipated advantage of developing such a system is the possibility of automating the monitoring and diagnostic processes for vibrating components, and building diagnostic systems which complement traditional PSD analysis by dealing with the non-linear characteristics of the signals.

This project deals exclusively with the analysis and classification of signatures coming from rolling element bearings in bench tests. Previously, we analyzed vibration data from rolling elements in a steel sheet manufacturing facility with excellent results[8]. The next phase of the project deals with the application of these techniques to electric motors and centrifugal, multicellular pumps in EDF power stations, the technique is applicable to a variety of components in a nuclear power setting without major redesign[9,10].

The feasibility of using Recirculation and Autoassociative Backpropagation networks for compression of spectral data has been established. Under this study we have achieved compression ratios of 3/1 while maintaining the statistical properties of the original patterns. The Recirculation network, in our opinion, provides a better mechanism for this compression. Our results to date indicate that the compressed version obtained from Recirculation is better suited for training the classifier networks.

Traditionally, diagnosis of components based on vibration analysis has been made by looking at specific regions of the spectra. We feel like the compressed signature is an efficient and feasible representation which provides complete information and allows the analysis to be made on a broader base. Complete information about the spectrum is important because vibration in general is imprecise. In some cases the behavior of components under certain operating states is not known in detail, especially when the behavior is induced by more than one fault.

Although our project is in the early state of development we feel that neural networks can provide a methodology for improving the analysis of spectra, and may provide a viable complement to PSD analysis for monitoring and diagnostics of vibrating components. Our results to date are very encouraging.

ACKNOWLEDGEMENTS

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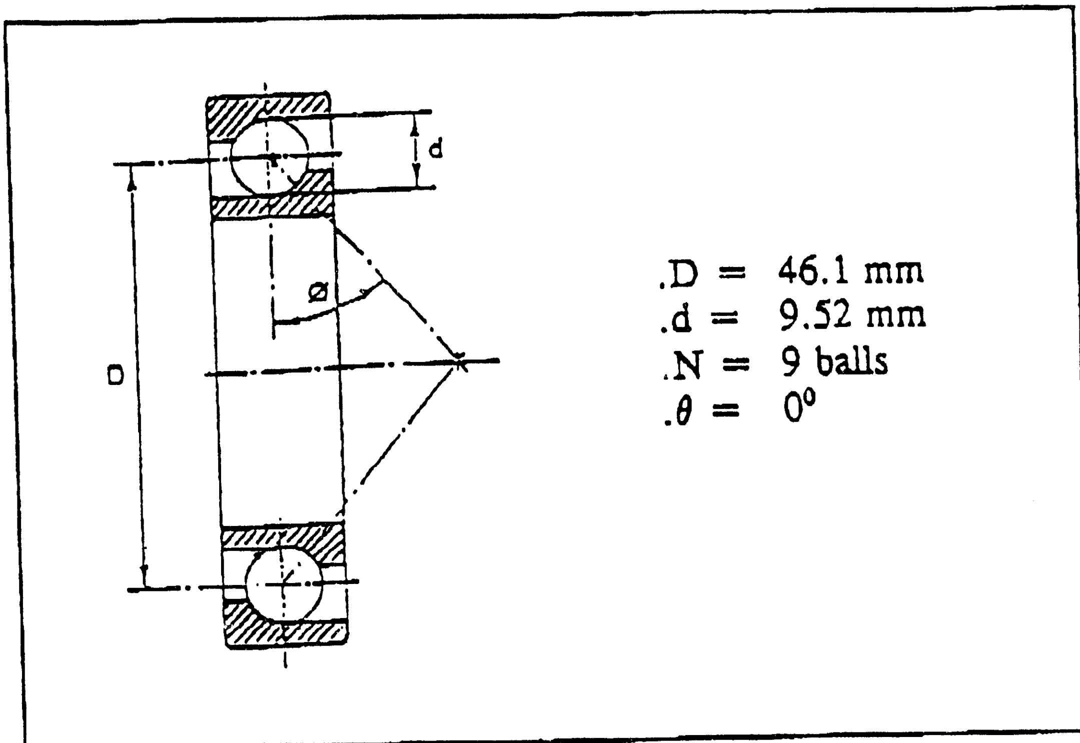

Figure 1. Geometry of a 6206 Bearing

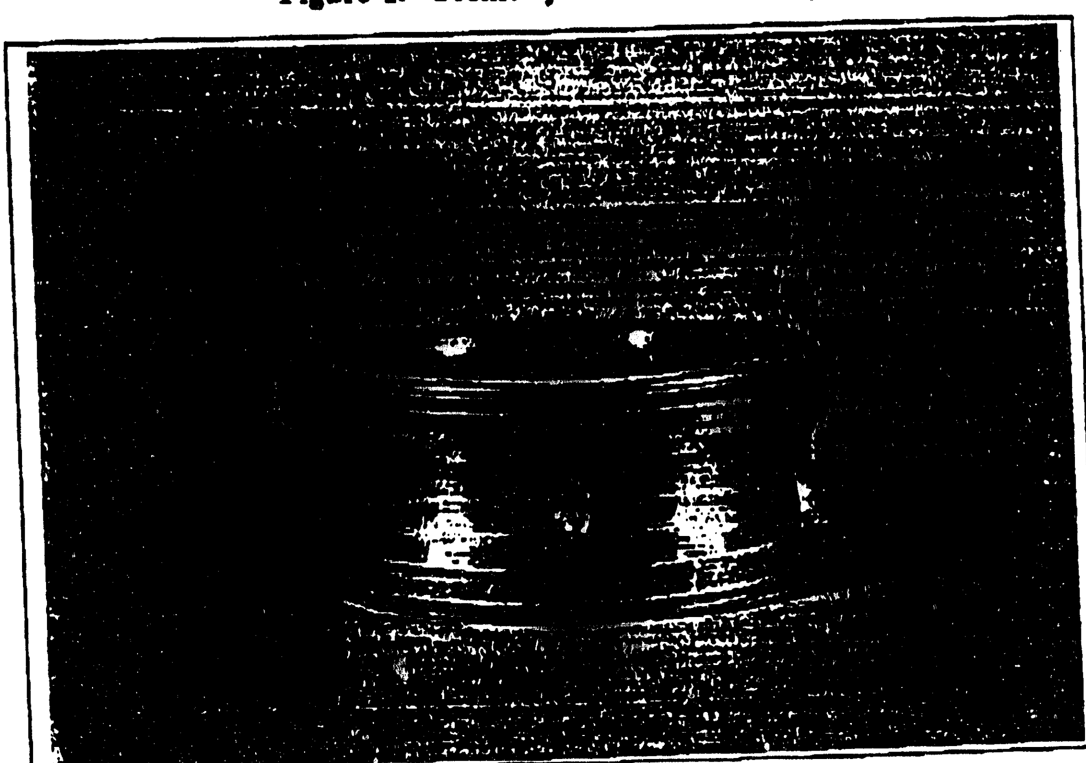

Figure 2. The Inner Race of a 6206 Bearing with a Localized Scaling Fault

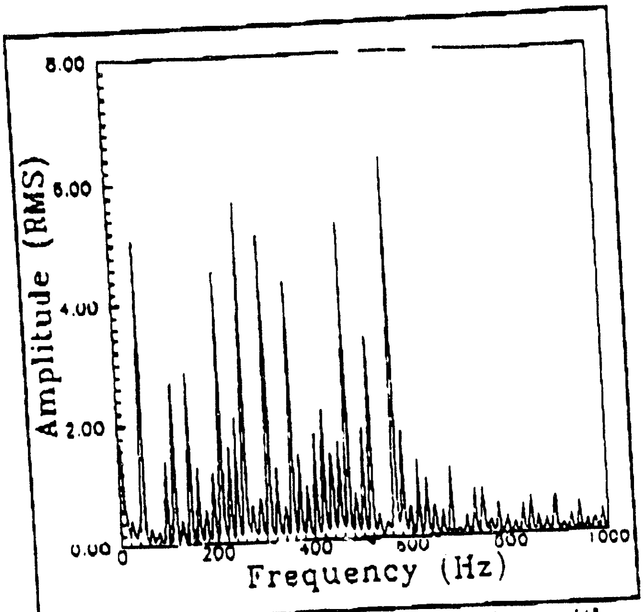

Figure 3. Spectrum of A Bearing with a Generalized Scaling Fault of the Inner Race

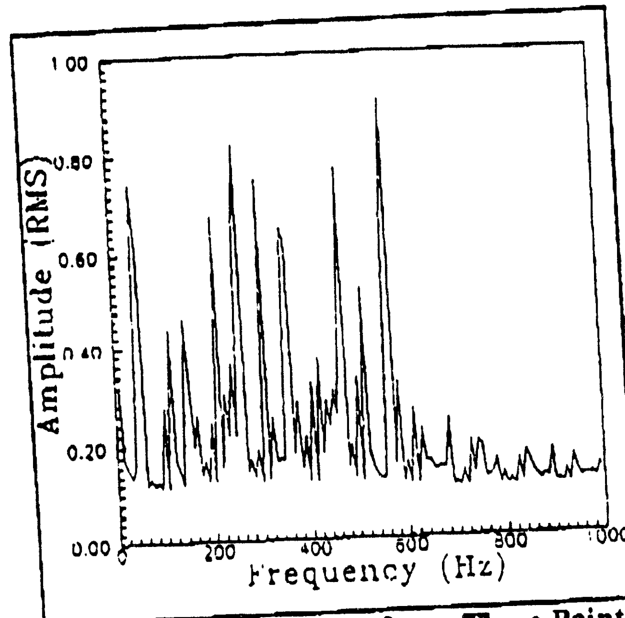

Figure 4. Maximum of Every Three Points from Normalized Signature (Figure 3)

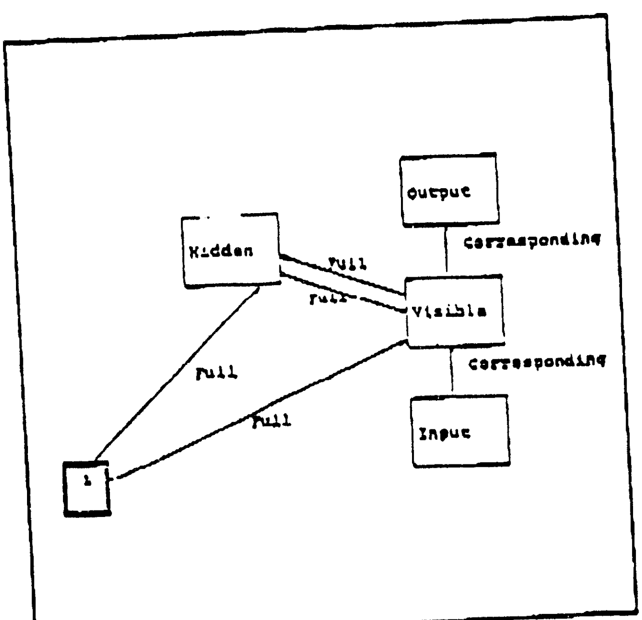

Figure 5. Topology of a Recirculation Network

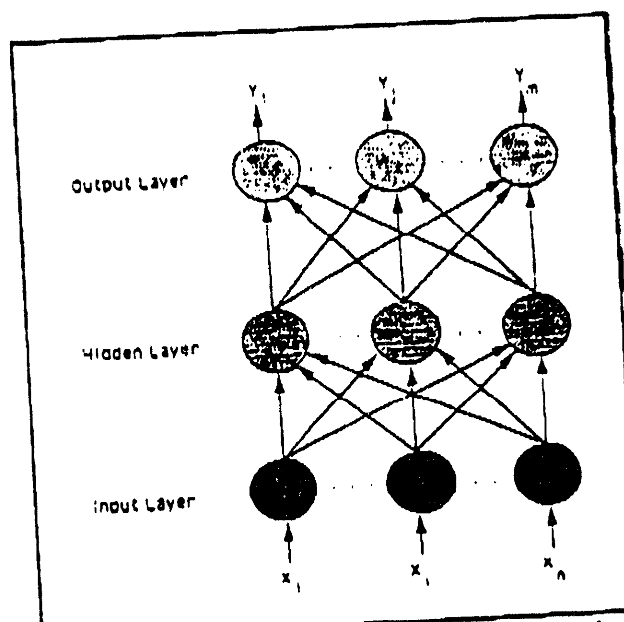

Figure 6. Topology of a Backpropagation Network

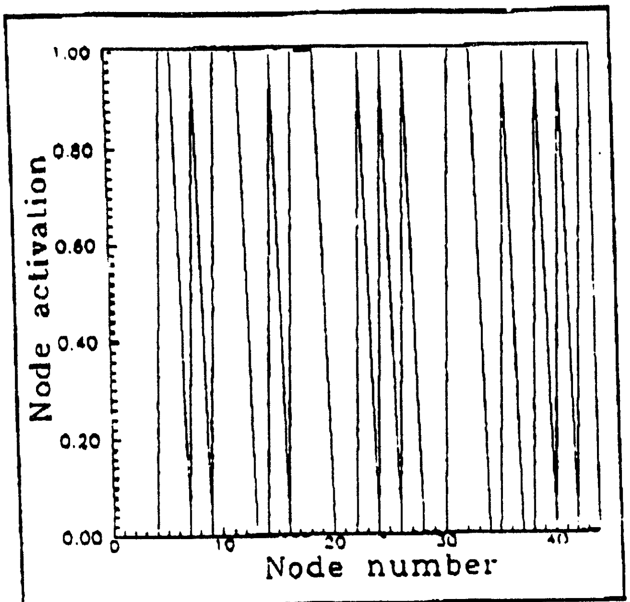

Figure 7. Compressed Signature Using RNN

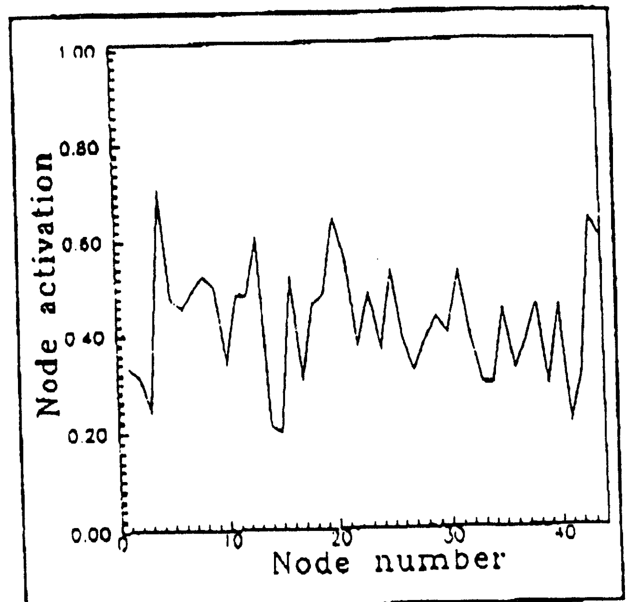

Figure 8. Compressed Signature Using BPN

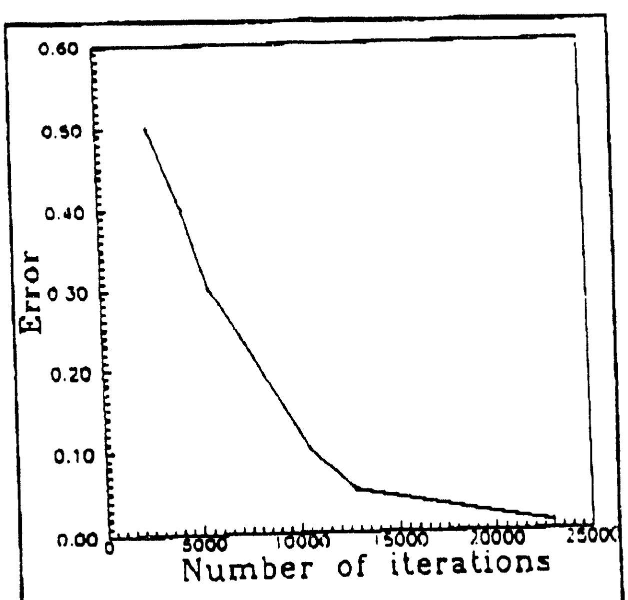

Figure 9. Training with the RNN Representation

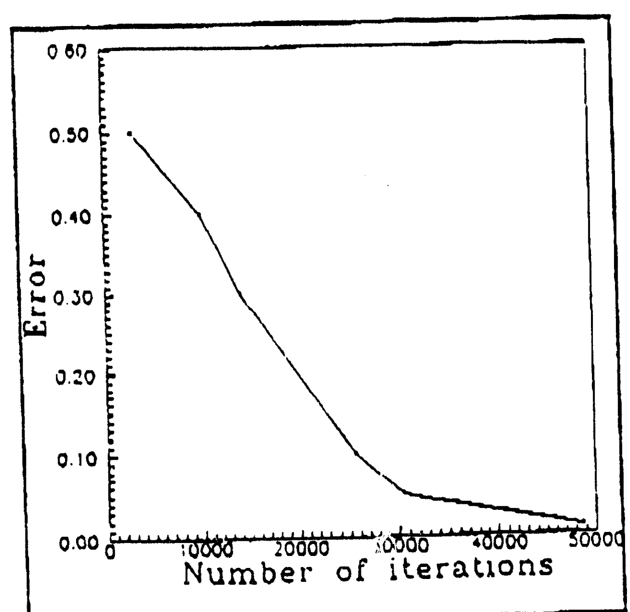

Figure 10. Training with BPN Representation

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