Diagnoses for Machine Vibrations Based on Self-Organization Neural Network

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Abstract: In this work, we develop a diagnostic system for the recirculating system of an on lined nuclear power station based on the neural network. In learning phase, signals of sensors which monitor the mechanical operation of the recirculating system are preprocessed mainly by spectrum analysis to produce sets of spatio-temporal patterns. The neural network serves the kernel of the diagnostic system of which the main function is to self-organize a feature map of these spatio-temporal patterns. Each spatio-temporal pattern here is a high dimensional vector composed of 128 elements, and, after self-organization, a reduced two dimensional feature map is established as composite diagnostic panel, called CDP. In the detecting phase, all monitoring signals are fed into the CDP. Geometrical behaviors of the CDP in detecting phase including representing cluster and traveling sequence of temporal signal of each sensor put our diagnoses into practice.

Introduction

The self-organization principles [1] are widely applied neural network principles. The neural phonetic typewriter [2] which successfully recognizes phonetic units from a continuous speech signal is a typical application. The spatial ordered maps in the self-organization are usually used to be internal representations of the input signals. The ordered relations in high dimensional inputs are reduced to express in a low dimensional map. We use the dimensionality-reducing mappings to practice the emergent spatio-temporal relations among the signals produced by sensors which monitor the mechanical behaviors of two pumps of the recirculating system of an on-lined nuclear power station.

Three dimensional position ,velocity, and acceleration are the main circulating information which sensors monitor. Diagnoses for the recirculating system are based on these information. The signals produced by sensors carry these information. But the signal in time domain are so native that operator in the control room of an on-lined nuclear power station is not able to judge the security of the operation by watching on the signals. Amounts of processes have to be applied to native signals to obtain more visible information based on which the operator can do some judge for the security.

By combining the technology of power spectral analysis in the field of digital signal process and the principle of artificial neural network, we develop a new diagnostic method for the recirculating system. The method contains three phases : spectrum analysis, CDP establishment, and CDP detection. Our basic idea is to put the native signals of sensors into visibility. Computer simulations show that the idea is a suitable approach to the requirement of visibility.

In this paper, we briefly review the self-organization principles in section 2 and then give details of the diagnostic design and computer simulatons in section 3. At last several conclusions are given.

Self-organizing neural network

Orderness of self organization is a structural phenomenon found in the fields of biology, society, and chemistry. Recently, the neural network with capability of self-organization play an important role in the development of neural computing. The self-organizing neural network proposed by Kohonen can form the localized responses by lateral feedback and the simplified virsion creates a vector quantizer.

In the self-organizing neural network, neurons with common input are arranged as a two dimensional array. Winner-take-all is the main principle of the self-organization. When feeding an input pattern, each neuron sums the weighted inputs and the largest responder is selected as the representative. And then, the neurons within the neighborhood of the representative adjust its weight vector toward the input vector. After enough input vectors have been presented, the weights will be organized such that topologically close nodes are sensitive to inputs that are physically similar. Output nodes will thus be ordered in a natural manner. The algorithm that forms feature maps requires a neighborhood to be defined around each node as shown in figure 1. The neighborhood slowly decreases in size with time as shown.

Above statements can be combined to following simple algorithm. For a randomly selected input vector $X(t)$ at time t do

a. Selecting the representative c:

$$\| X(t) - M_c(t) \| = \mathrm{MIN} \{ \| X(t) - M_i(t) \| \} \quad (1)$$

Where $M_i(t)$ denotes the weight vector of neuron i .

b.Updating weights:

$$M_i(t+1) = M_i(t) + \alpha(t)\,(X(t) - M_i(t)) \quad \text{for } i \in N_c(t)$$

$$M_i(t+1) = M_i(t) \quad \text{for all other indices } i \qquad (2)$$

Where the learning rate $\alpha(t)$ and the neighborhood set Nc(t) are empirical functions of time.

Diagnostic Process

The diagnostic process includes three block functions: spectrum analysis, CDP establishment , and CDP detection. The time domained signals of the sensors are translated into frequency domained power spectrum by using modern spectral estimation [3], which use precise objective functions or models of the underlying random process to achieve higher resolution, smoother estimates, and lower variance. In order to establish the CDP, we adopt the monitoring signals in the period from the starting-up to stable operation of the diagnosed system and then process these signals to form a set of input patterns for the self-organizing neural network. The mechanical operation in above period is called reference operation which is distinguished from the object operauon in the stage of CDP detection.

For the monitoring signals of each sensor, the preprocess include following function:

1.Recording the monitoring signals of the referenceoperation at about 400 seconds on a VHS tape.

2.Using analog to digital converter to upload signals to amicrocomputer.

3. Forming 20 segments with equal size.

4.Analyzing each segment of data by spectrum estimation,computed every 2 ms using a 512 ponit of hamming window.

5.Compressing and normalizing the first page of the powerspectrum of each segment into a 128 point of input vector.

Figure 2 is the 3-D power spectral diagram of one segment of one sensor. After preprocessing, each sensor creates 20 input vectors.

Based on the reference operation, we attempt to establish a CDP with ability to detect the variation , or abnormality of the object operation. In our idea, the CDP really searves a typical classifier in the level of sensor or segment. For the classification of sensors, after self-organization, the established CDP is expected to form closed geometric areas, one for each sensor. When feeding one input pattern created by a particular sensor, the largest responder in the CDP ought to lie within the scope corresponded to the sensor. If not so, the object operation maybe abnormal. The following illustrative simulation employs 32x32 neurons to capture the spatial features of 80 patterns created by four sensors of one pump. By using the existing algorithm described in section2 , 80 patterns are embeded into the weight matrix of the neural array to establish a composite diagnostic panel. The empirical function $N_c(t)$ and $\alpha(t)$ are both nonincriminating functions. $\alpha(t)$ denotes the learning rate which is set to a larger value in the phase of initial formation of the correct order of the map and to a small value in the phase of final convergence of the map into asymptotic form. A good self-organization thoroughly partition the CDP into areas with number of the employed sensors. Figure 3 is the result of the established CDP on which four areas are formed and each corresponds to one particular sensor. Each point represents a neuron in the figure. After self-organization,if a neuron is the representative of any pattern belonged to one sensor, we label the neuron with the number of the sensor. In this example, no two neurons are labeled with two different numbers.

The other crucial characteristic of the CDP is the traveling sequence of each sensor. The twenty training patterns of every employed sensors orderly fed into the CDP, the winners corresponding to each pattern form a fixed path, called traveling sequence. Figure 4-7 show the traveling sequence of the reference operation of the four sensors and in the figures English letters denotes the time order. We find there is no letter 'a' in figure 5, because pattern 1 and pattern 2 of sensor 1 have the same representative. In the stage of CDP detection, the traveling sequence of each sensor of the object operation is expected to match the captured traveling sequence of the same sensor in the reference operation. In figure 8, the neurons are labeled with the number of the patterns to which they learned to give the best reponses. Figure 9 shows the same information as figure 8, but the CDP only trained by the patterns created by sensor 1. The one sensor's CDP give more reliable diagnoses by property of traveling sequence in the CDP detection.

Conclusion

The self-organizing neural network has been applied to the prototype of a diagnostic system for the recirculating system of an on-lined nuclear power station. The on-lined signals are adopted as typical operation based on which the composite diagnostic panel are established by using the winner-take-all principle. Some characteristics of the trained composite diagnostic panel are crucial to the diagnoses. Computer simulations show some useful geometric properties of the composite diagnostic panel in detecting phase. However more experiences combined with expert knowledge of nuclear power system are needed to develop the prototype with improvements.

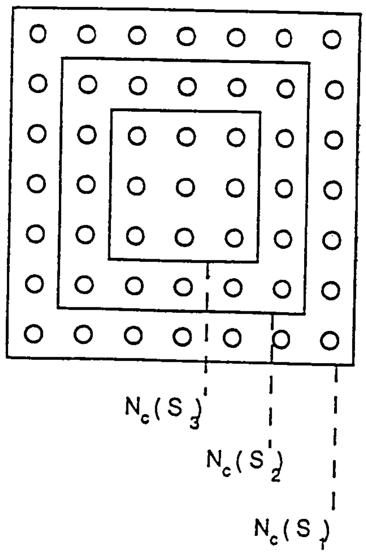

Figure 1.Topological neighborhoods at different times as feature maps are formed. $N_c(S_j)$ is the set of nodes considered to be in the neighborhood of node j at time t. The neighborhood starts large and slowly desreases in size over time. In this example $s_3>s_2>s_1$.

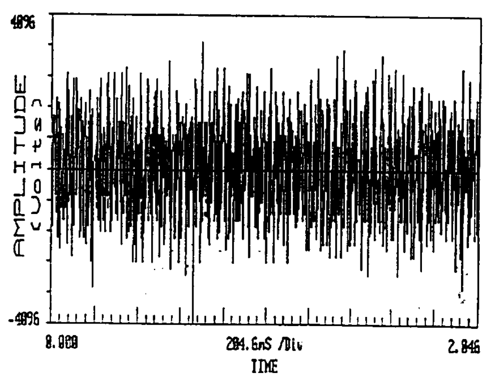

Figure 2.a Time domianed signal of the tenth segment of sensor 1.

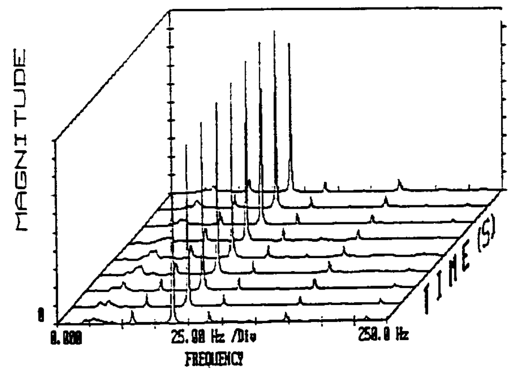

Figure 2.b The 3-D power spectral diagram of the tenth segment of one sensor is generated by ML1 method with 128 lag. There are 10 continuous pages, plotted from outer to inner. two closed pages are overlapped with 512 points.

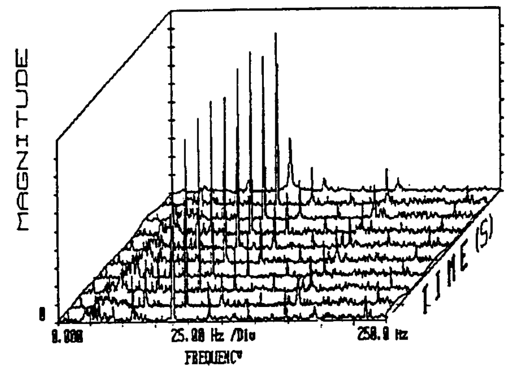

Figure 2.c The 3-D power spectral diagram of the tenth segment of one sensor is generated by FFT method .There are 10 continuous pages, plotted from outer to inner. two closed pages are overlapped with 512 points.

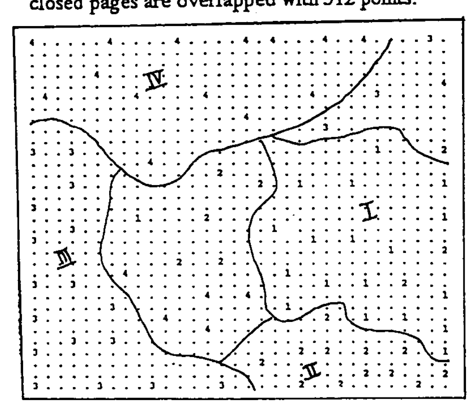

Figure 3. Four larger areas of the CDP circled by the curve are belonged to four sensors correspondingly. The labeled neuron is the representative of some pattern belonged to the number of the sensor.

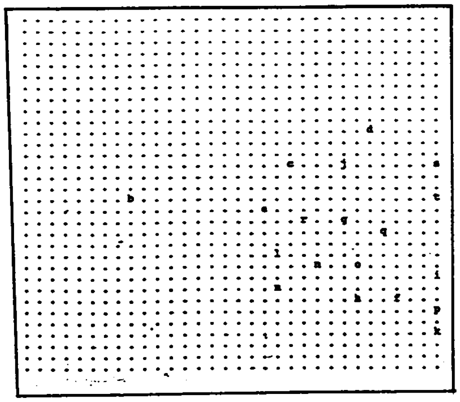

Figure 4. The traveling sequence of the reference operation of sensor 1 with order a < b < c.

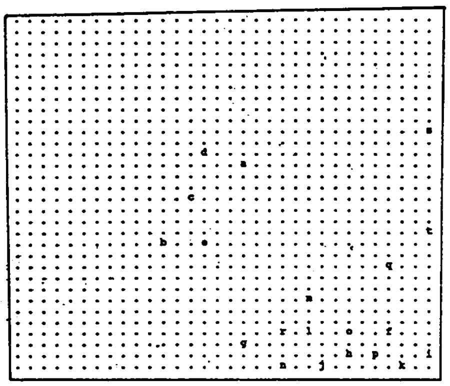

Figure 5. The traveling sequence of the reference operation of sensor 2 with order a < b < c.

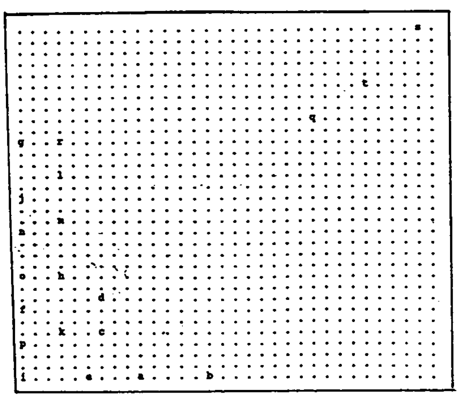

Figure 6. The traveling sequence of the reference operation of sensor 3 with order a < b < c.

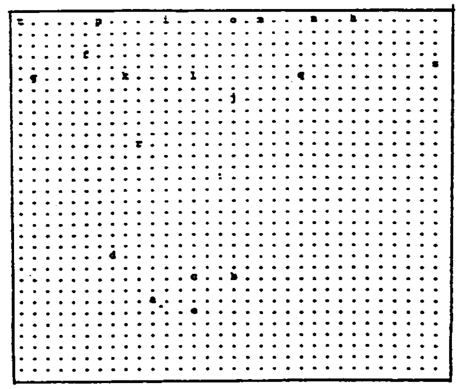

Figure 7. The traveling sequence of the reference operation of sensor 4 with order a < b < c.

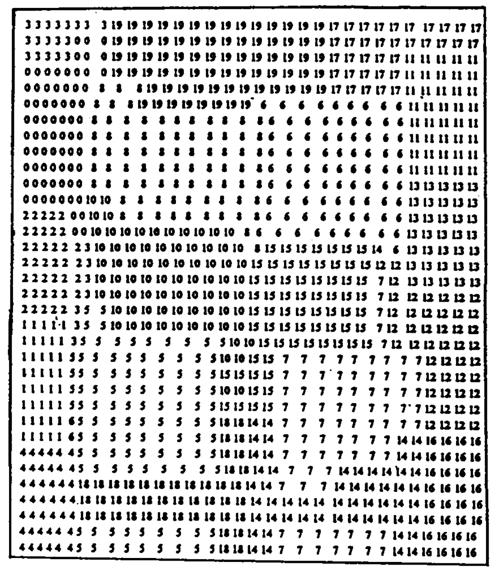

Figure 8. The neurons are labeled with the number of the patterns which they learned to give best responses.

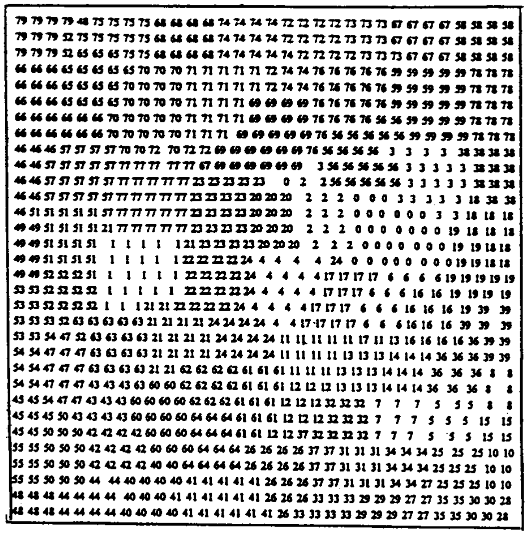

Figure 9.The one sensor's CDP is trained by the patterns created by sensor 1. The neurons are labeled with the number of the patterns which they learned to give best responses.

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[2] T.Kohonen, K.Masisara and T.Saramaki, "Phonotopic Maps-Insightful Representation of Phonological Features for Speech Representation" Proceedings IEEE 7th Inter. Conf. on Pattern Recognition,Motral, Canada, 1984.

[3] C.Y. Liou , B.R. Musicus, " A Separable Cross-Entropy Approach to Power Spectral Estimation" IEEE ASSP, Vol. 38, No. 1,Jan 1990.