Transactions on Information and Communications Technologies vol 16, © 1996 WIT Press, www.witpress.com, ISSN 1743-3517

Diagnosis of rotating systems using artificial neural networks

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Abstract

Vibration monitoring of components in manufacturing plants involves the collection of vibration data, and a detailed analysis of data. One of the most important characteristic of neural networks is their ability to model process and systems from actual data, and to respond in real time to the changes in the machine state. This paper discusses the use of neural network for fault classification in rotating systems using signal of vibration.

1 Introduction

The analysis of vibration monitoring of components detects and reflects the main operational state of the machinery. Vibration in mechanical systems may provide several information about the various equipment of the manufacturing plants. There are good references in the literature that describe the type of signal of vibration associated with typical faults of the systems and the techniques of analysis that can be used to detect the fault in an early state. Analysis of tendency, for example, is performed by comparing the vibration spectrum of each machine with a reference spectrum, and evaluating the vibration magnitude changes of each spectrum at specified time.

The diagnostic methods can be divided into two groups: one that evaluates the operation state of the system and classifies it in satisfactory or unsatisfactory and those that detect the type of the fault. The first group is based on standards that describe the limits of vibration levels of a given class of machines. The second one does not present standards of comparison, since it depends on the use, i. e. each method is better adapted to specific characteristics of the machine. Those methods based on standard of comparison measure the vibration spectrum of the machine, which has a characteristic shape when it is operating properly, and compare with a standard level since the characteristic of signal are different when the machine is not operating satisfactorily.

These two classical pattern recognition techniques, in some cases, seem to be not powerful enough and the application of neural nets can improve this technique. In this case, the use of classical pattern makes apparent the need of robust pattern parameters and representative mathematical model designed in the context of vibration analysis, able to integrate and manipulate the vibration problem.

In classical pattern recognition techniques, a significant part of the analysis consists in the preprocessing and important characteristics can be extracted from the data which can be separated them in sets of data related with each kind of fault. This classification of data in different kinds of faults can be regarded as the main problem.

These forms of analysis for diagnosis are performed by maintenance personal monitoring and recording transducer signals and analyzing the signals aiming at identifying the operating condition of the machine, and incipient faults. Therefore, there is considerable motivation to design systems that automatically perform this type of analysis on real time and in a reproducible manner. The success of any monitoring program depends on the accuracy of the measurements that affect, directly, the ability of the system to detect and identify faults. Accelerometers are a popular transducer for vibration analysis due to their accuracy, light weight, and wide range frequency response.

Neural networks have recently been created as an excellent and powerful tool for pattern recognition and can be applied for fault detection in machinery. Neural nets provide a viable technique for the analysis of vibration data because of their inherent ability to operate on noisy, incomplete or sparse data and to model process from actual system parameters, Uhl [1].

The presence of noise can complicate the monitoring task by altering the true signal, and by increasing the vibration values beyond of a specified level. When a machine is operating properly, vibration is small and constant. However, when faults develop and some of the dynamic process in the machine change, the vibration spectrum also changes. For many machines, the vibration frequency spectrum has a characteristic shape when the machine is operating properly, and it presents different characteristics when it operates with faults. Therefore, monitoring of the operating conditions of the machine can effectively be performed by a close examination of the features associated with particular faults and their identification.

We are interested in the identification of faults from frequency analysis domain, but application of this methodology is similar by any other kind of signal. The frequency spectrum, is useful because the low level signal are not masked out by the presence of high level signal, when using a log scale. Generally, each machine defect produces a set of vibration components that allows the recognition of different faults. There are many parameters that can be measured to evaluate the operation condition of a machine, for example pressure, temperature, sound, oil particles, etc.

Vibration signals can be processed in a variety of ways, and typical faults in rotating machine that can be identified are: misalignment, characterized by a peak at two times the running speed (2.n); unbalance, vibration at n; gear problem, gear mesh frequency; mechanical looseness; bearing faults; eccentricity; oil whirl; and other.

2 Methodology

Neural networks may be designed to classify input patterns in pre-defined classes or to create categories of group patterns according to their similarity. One of the most important characteristic of neural networks is their ability to model process and systems from actual data, and to respond in real time to the changes in the system state, provided by continuous sensor inputs. For complex system, the fault identification in real time can be facilitated by applying this methodology.

An ANN, therefore, comprises a set of neurons interconnected and organized in layers. Some examples are discussed in literature [2], [3]. It is made up of a given number of layers, each of which has a specified number of neurons. The interconnections are only between neurons of adjacent layers, and each node (neuron) belonging to a layer is connected to all the neurons of adjacent layers. The neurons connected directly to the network inputs all belong to the same layer, called as the input layer, these neurons do not have offset. The neurons that furnish the network outputs also belong to a single layer, called the output layer. The other neurons are organized in one or more layers, called hidden layers, because they can not directly be reached from outside the network.

It should be noted that the number of neurons for the input and output layers depends on the specific application. The choice of the layer number and dimension is based in preliminary tests, and optimizing this choice is a significant topic in the studies of artificial intelligence researches, Bernieri [4].

The ANN is capable of learning by example. The network is forced to furnish the desired outputs on the basics of the inputs supplied to it. This is carried out through learning algorithms, which suitably modify both the interconnection weight and offset values. Once learning is complete, the neural network is capable of furnishing the desired outputs for the known inputs.

The problem of identifying and classifying vibration signals can be divided in three stages: I. separation of the signals of components operating normally and signals of components with fault; II. compression of the signals; III. classification of the compressed patterns using backpropagation algorithm. Compression has an important issue in the context of this methodology, because it transforms a large data set in a reduced set with the same information, and decreases significantly the training time.

3 Neural Networks

Neural networks is made by a number of processing elements which are connected to form layers of neurons. Each neuron is a simple mathematical processing unit that when are interconnected, produces a complex structure and once trained, it can provide the ability to execute some tasks. The scheme of proposed diagnostic system is shown in figure 1.

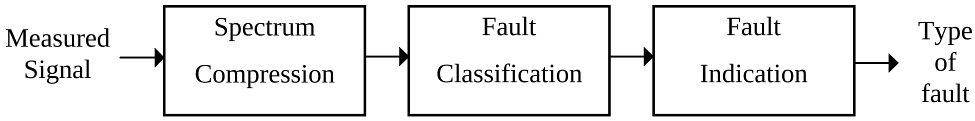
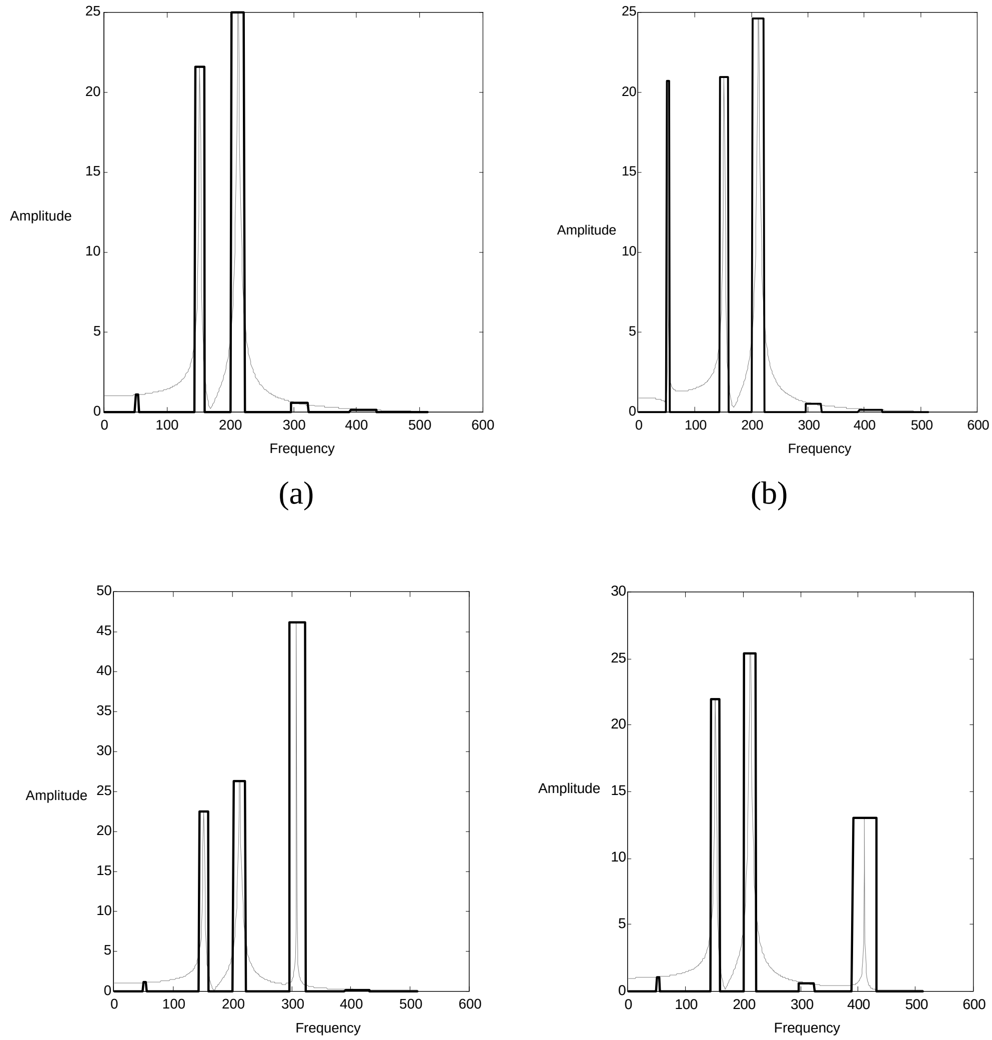


Figure 1: Scheme of proposed diagnostic system

The first step in the diagnostic procedure consists in spectrum size reduction, which contain 512 points in the original form. Two methods have been applied in this paper. The first method divides the range of frequency in intervals of five points. From each interval, the maximum amplitude is selected and this point is used to construct a new signature. The second method searches the maximum points in the original signal for each frequency range early specified, i.e., around of the natural frequencies and of the fault characteristic frequencies. It is considered a range of 10% of the frequency for each maximum point.

Figure 2 shows the original (512 points) and compressed signal (masked), with 27 points.



(a) (b)

(c) (d)

Figure 2: Original and compressed signal

Figure 2.a shows the signal of the machine without fault , and the two natural frequencies (152 and 222 Hz). Figure 2.b shows the signal with the natural frequencies and one fault, characterized by a peak in the frequency of

51 Hz (will be called **fault 1**). Figure 2.c shows the signal with the peak in 308 Hz (**fault 2**). Figure 2.d shows the signal with the peak in 411 Hz (**fault 3)**.

It is common to specify an architecture by referring to the number of hidden layers; layers that are neither inputs nor outputs. The figure 3 shows the architecture used in this case. It has one hidden layers, with 5, 10, 20 or 50 neurons and output with two elements. The network is trained so that output is a combination of 0 and 1 depending on the machine condition.

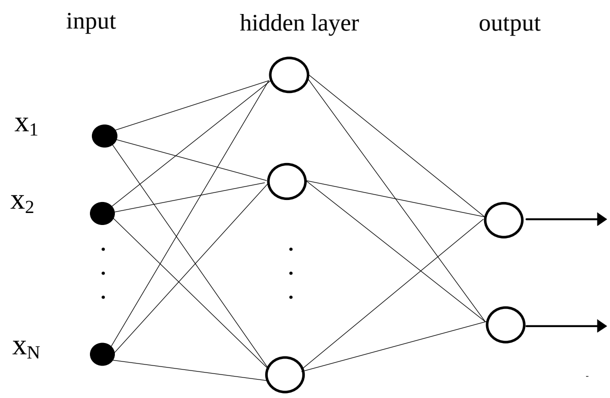


Figure 3: Architecture of the neural network with one hidden layer

The input with weight $w^h_{j,i}$ and bias, b^h_j , is added and the result is fed to the hidden layer. The input to the *j*th hidden unit is:

$$I_j = b^h_j + \sum_{i=1}^{N} W^h_{j,i} . x_i \tag{1}$$

where the superscript (h) means that the quantities pertain to the hidden unit. Simplifying, the output of the net is a biased and weighted sum of the hidden layer outputs:

$$y_{out} = b^o + \sum_{j=1}^{H} W_j^o . HO_j \tag{2}$$

the superscript (o) referring to the output unit, H is the units number in a hidden layer and HO_j is the output of the *j*th hidden unit. The net is trained starting with a random set of weights and biases and calculating the output for every input sets. Then the error, *E*, is evaluated and as it is computed from the output layer backwards, it has historically been called the backpropagated error, and the learning algorithm the backpropagation. This algorithm can be found in several publications, for example [5]-[7].

$$E = sumsqr(T - y_{OUT}) \tag{3}$$

where sumsqr is the sum of squared elements and T is the desirable output. The error, *E*, is taken as a function of the weights and biases and then, the minimization is performed by means of the usual steepest algorithm. The error, E, is taken, for convenience, as a function of the $\{\alpha_i\}$, the index *i* taking on as many values as there are weights and biases. When the parameter, α_k, changes by $\delta\alpha_k$, the error, E, changes by

$$\delta E = \frac{\partial}{\partial \alpha_k}(E).\delta\alpha_k \tag{4}$$

where $\frac{\delta}{\delta\alpha_k}(E)$ is evaluated using the current values of the parameters. To ensure that changes in α_k results in a decrease in E, we select

$$\delta\alpha_k = -\eta \frac{\partial}{\partial \alpha_i}(E) \tag{5}$$

where η is a positive constant. The parameter η determine how large a step is made in the direction of steepest descent and therefore how quickly the optimum parameters are obtained. For this reason η is called the learning coefficient.

The training net use a set of input for which a specified output are known. Table 1 shows the results obtained from compressed data. SSE( ) is the Sum Squared Error between the value output that the network was trained and the value that was obtained with a specify input. Third column shows the results when the input was a signal simulating a undamaged machine, to the hidden layer with 5, 10, 20 and 50 neurons. By the others columns, the proceeding is similar, i.e., the fourth column shows the results by a signal simulating the fault 1, and so on.

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Table 1. Results obtained to compressed data

		Undamaged	Fault 1	Fault 2	Fault 3
N = 5	SSE(1)	**0.00001**	0.00001	0.89799	0.00001
	SSE(2)	0.00926	**0.00001**	0.05911	0.01728
	SSE(3)	1.53039	1.53039	**0.00001**	1.52020
	SSE(4)	0.30628	0.33609	1.52777	**0.00001**
N = 10	SSE(1)	**0.00001**	0.00426	3.90372	0.00039
	SSE(2)	0.02950	**0.00001**	0.35177	1.20097
	SSE(3)	0.05461	1.27712	**0.00001**	0.00558
	SSE(4)	0.43607	0.27086	0.09322	**0.00001**
N = 20	SSE(1)	**0.00000**	0.16492	0.66831	0.28279
	SSE(2)	1.61329	**0.00000**	0.42521	0.47416
	SSE(3)	2.21279	5.97149	**0.00000**	2.98080
	SSE(4)	0.83841	0.14143	2.64771	**0.00001**
N = 50	SSE(1)	**0.00000**	1.20186	39.75560	2.09704
	SSE(2)	11.48372	**0.00001**	4.90336	0.65161
	SSE(3)	1.93938	8.25439	**0.00000**	3.85028
	SSE(4)	2.21215	2.98644	1.07212	**0.00001**

Figure 4 shows the results of the up table in a graphic form.

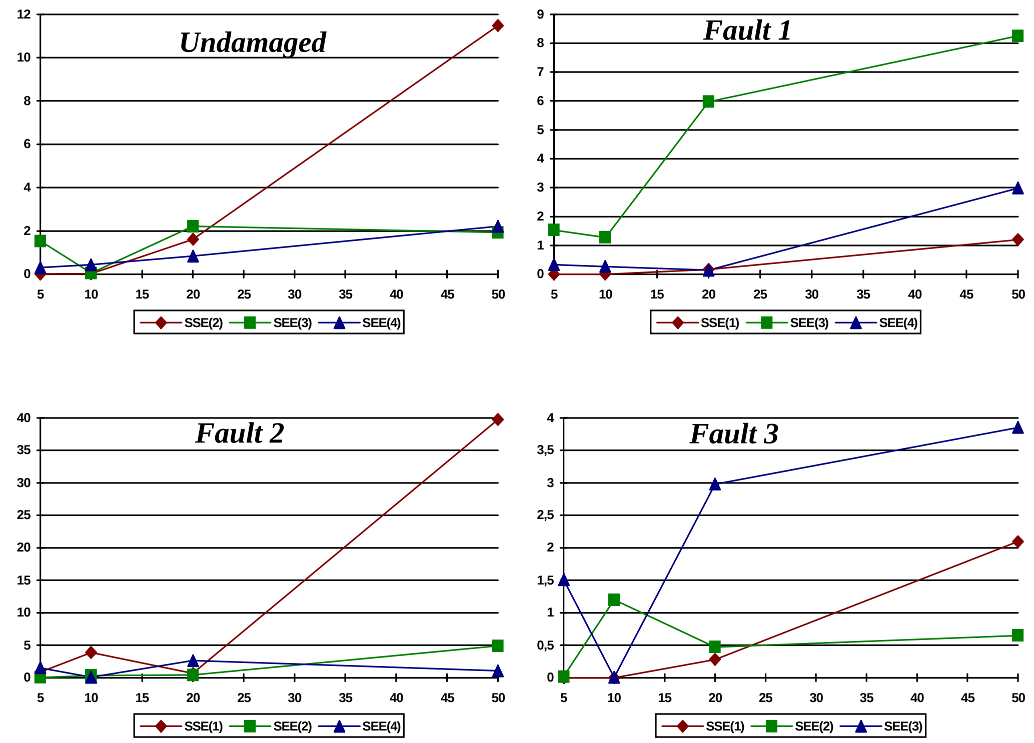

Figure 4: Confrontation to hidden layer with 5, 10, 20 and 50 neurons.

4 Conclusion

The paper discusses the use of neural network for fault classification in machine. The compressed data considering a range of 10% of frequency, seems to be more adequate because it considers every peak of amplitude when there is variation in operation speed of machine. There is not a consistent criteria for determining the optimum architecture of the net, as can be seen by figure 4, but in general SSE( ) increases when the neurons number in the hidden layer is great. As can be seen in table 1 or in figures 4, this methodology can be applied to classify an unknown signal in patterns previously fixed.

Key words: Neural network; Predictive maintenance; Fault classification

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